REPORT DOCUMENTATION PAGE	Form Approved OMB NO. 0704-0188

1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (From - To)
15-04-2015	Ph.D. Dissertation	-

4. TITLE AND SUBTITLE
Use of EEG to track visual attention in two dimensions

5a. CONTRACT NUMBER
W911NF-08-1-0148

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER
611103

6. AUTHORS
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5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES AND ADDRESSES
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8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS (ES)
U.S. Army Research Office
P.O. Box 12211
Research Triangle Park, NC 27709-2211

10. SPONSOR/MONITOR'S ACRONYM(S)
ARO

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
54228-LS-MUR.46

12. DISTRIBUTION AVAILIBILITY STATEMENT
Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES
The views, opinions and/or findings contained in this report are those of the author(s) and should not contrued as an official Department of the Army position, policy or decision, unless so designated by other documentation.

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15. SUBJECT TERMS
EEG attention vision

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	15. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Thomas D'Zmura
UU	UU	UU	UU		19b. TELEPHONE NUMBER 949-824-4055

Report Title

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University of California, Irvine

Doctoral Thesis

Use of EEG to track visual attention in two dimensions

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Supervisor

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in Psychology

in the

School of Social Sciences

May, 2014

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Table of Contents

List of Symbols and Abbreviations

Degrees of Visual Angle	º
Advanced NeuroTechnologies	ANT
Bits-Per-Minute	BPM (a unit of ITR)
Brain-Computer Interface	BCI
Confidence Interval	CI
Common Spatial Patterns	CSP
Number of data features (Dimensions)	d
Electroencephalography	EEG
Electromyography	EMG
Event-Related Potential	ERP
Event Related Desynchrony/Synchrony	ERD/ERS
Functional magnetic resonance imaging	fMRI
Hertz	Hz
Inter-Stimulus Interval	ISI
Information Transfer Rate	ITR
Regularized-Bayesian Linear Discriminant Analysis	LDA
Magnetoencephalography	MEG
Milliseconds	msec

Number of Trials/Data	N
Random Forest	RF
Steady-State Visual Evoked Potential	SSVEP

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Experiment 1

Experiment 2

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Acknowledgements

This research was supported by ARO 54228-LS-MUR.

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TunedIT.org & Warsaw University of Technology, June 2011

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Abstract

This thesis investigates the use of EEG to track the spatial locus of covert, visual attention. Three experiments are described that were to detect the position of visual attention as it was deployed towards targets as they appeared. The first experiment uses flickering fields placed in the periphery of the visual field to induce SSVEPs, to be used to track the position of attention which varies horizontally between them. The flickers failed to produce significant SSVEP activity. However attention locus could still able to be tracked by endogenous lateralizations of 12Hz and 18Hz activity. A second experiment was then designed to track attention locus as it varied either horizontally or vertically using only endogenous EEG activity in the alpha (10Hz), low-beta (18Hz), high-beta (24Hz) and gamma (36Hz) bands. Tracking proved successful in all but a small number of subjects. Horizontally varying attention was associated with lateralizations of the alpha band and low-beta band, while vertically varying attention was associated with varying alpha band and low-beta band activity in the occipito-parietal junction over the central sulcus. A third experiment was then performed to track attention locus as it varied in two dimensions. Using a combination of the features found to be informative in the second experiment, tracking proved successful in up to nine bins of two-dimensional visual space. Tracking in either the horizontal or vertical dimension was also successful when attention varied in two dimensions. The success of this method shows that EEG can be used to passively detect the spatial position of attention, at varying degrees of position, as a person attends to objects they see.

I. Introduction

Research into visual attention as a control signal for brain-computer interfaces (BCIs) is well into its second decade (He *et al*. 2013, Lotte 2005, Müller-Putz *et al*. 2005, and Wolpaw *et al*. 2002). Technologies to communicate using signals originating directly from brain activity have been primarily targeted towards persons with debilitating neurological conditions that disable all muscle movement (Birbaumer *et al*. 2008, Wolpaw *et al*. 2002). Because of this particular population of interest, attention-based BCI research has relied upon users manipulating what is referred to as "covert" attention or attention directed to sensory inputs without the use of orienting muscle movements such as saccades or head movements. There is a wealth of results on this mechanism of visual attention (Bressler *et al*. 2008, Corbetta and Shulman 1998 & 2002, Posner *et al*. 1980, Shipp 2004, Wojciulik and Kanwisher 2000). Most work on attention-mediated BCIs has focused on the visual modality, although there is also work on directed auditory (Horton *et al*. 2013, Horton *et al*. submitted) and somatosensory attention (Kaufmann *et al*. 2013, Müller-Putz *et al*. 2006, and Zhang *et al*. 2007).

BCI research on visual attention has produced several methods for using brain activity for control (Gerven and Jensen 2009, Lin *et al*. 2006, Marchetti *et al*. 2013, Müller-Putz *et al*. 2005). BCIs that use visual attention for control require either specialized, external stimuli to induce event-related potentials (ERPs) or endogenous brain activity associated with directed covert visual attention. BCIs that use ERPs have a much longer history, and have produced the highest information transfer rates (ITRs) to date (Bin *et al*. 2009). However, the use of endogenous brain signals by BCIs has advantages over methods that rely on ERPs. First, detecting endogenous patterns of brain activity eliminates any obtrusive visual stimuli that are needed to induce ERPs. Second, using the endogenous signals generated by mechanisms of covert attention lets users direct attention throughout the visual field in a natural way. Third, attention is innately associated with interest and intent, and to what attention is directed is typically the signal of interest for BCIs. Using a BCI to detect what draws someone's attention is far more informative and useful than making someone choose between predefined targets.

BCIs that use endogenous brain signals associated with the direction of visual attention were introduced by Kelly and colleagues (2006). These systems use EEG or MEG to detect lateralization of alpha-band and beta-band activity associated with the orientation or position of the locus of attention. The strength of alpha band lateralization has been positively correlated with both the eccentricity of the locus of attention (Bahramisharif *et al*. 2011) and improved performance in visual discrimination (Haegens *et al*. 2012). EEG BCIs have been designed to use these features for many purposes (Kelly *et al*. 2005, Ricco *et al*. 2012, Thorpe *et al*. 2012, Tonin *et al*. 2012 & 2013). MEG-signal based BCIs can discern two spatial dimensions in the direction of visual attention (Bahramisharif 2011, Gerven and Jensen 2009) and estimate the polar angle of locus of attention continuously (Bahramisharif *et al*. 2010). Though MEG methods have been able to out-perform their EEG counterparts in degrees of freedom and ITR, EEG has obvious practical advantages.

EEG-based BCIs that use endogenous signals related to covert visual attention use the experimental paradigm developed by Posner (1980). This paradigm targets top-down mechanisms that deploy attention to a region of visual space in which visual stimuli are absent. Assessing top-down attention in this way eliminates the influence of bottom-up stimulus-driven brain activity. EEG studies of this kind report accuracy rates in the low 80% range for the best-performing subjects in one dimensional, horizontal, binary classification (Ricco *et al*. 2012, Tonin *et al*. 2012 & 2013).

However, deploying attention to empty space is not a natural behavior, and most individuals are not adept at controlling top-down covert, visual attention in the way needed by these BCIs. Attention is used to enhance incoming sensory information and is usually deployed towards targets of interest. For covert visual attention BCIs to leave the laboratory and allow users to transmit intent about the rich visual world around them, a better design would be to capture attention as it interacts with unaltered, incoming visual stimuli and transmit either features of said stimuli or the spatial locus of deployed attention. The goal of such a BCI would not be trial-based transition of a discrete choice, but the continuous tracking of the locus of attention.

Three EEG experiments will be described that investigate both the SSVEPs and endogenous signals related to visual spatial attention, with the goal of passively tracking the locus of attention. The first experiment introduces a new way to use flickering stimuli, placed at the periphery of the visual field, to induce SSVEPs. The aim was to use the highly-detectable SSVEP while avoiding the drawbacks of centrally placed flickering stimuli. The experimental hypothesis was that the magnitude of the SSVEPs would be modulated by the visual attention system in a way that depends on the proximity of the covert attention locus to flickering stimuli. These locus-dependent modulations would then be used to passively track the spatial location of visual attention.

The second experiment was designed to determine whether the spatial locus of visual attention can be tracked using only endogenous brain activity. The analysis sought to characterize the endogenous brain activity associated with attending to visual targets that varied in position along a single dimension, either horizontally or vertically, and then to track the spatial position with predictive models.

The third experiment, like the second, was designed to determine whether endogenous brain activity can be used to track the locus of visual attention passively. However, this time, the positions of the attended targets varied in two dimensions. Tracking was then attempted in either one dimension at a time or in two dimensions simultaneously.

II. Using SSVEP to track attention to visual targets that vary in their horizontal position

Introduction

EEG BCIs use one of four brain signals to detect intent: slow cortical potentials (SCP); event-related synchrony or desynchrony (ERS/ERD) associated with mental tasks like imagining motor movement or directing covert visual spatial attention; ERPs triggered by stimuli like the p300 associated with the appearance of an anticipated an anticipated stimulus, or steady-state visual evoked potentials (SSVEPs) induced by flickering visual stimuli and modulated by visual attention (Bin et al. 2009 and Riccio et al. 2013, Tonin et al 2012 & 2013, Wolpaw et al. 2002, Wolpaw and McFarland 2004). The most successful in terms of information transfer rate (ITR) have certainly been SSVEP-based BCIs. These systems typically report accuracy rates above 99% when distinguishing between a user's attention to one of the discrete, flashing targets, yielding ITRs of above 60 BPM (Bin et al., Burke et al. 2005, Lalor et al. 2005, and Kelly et al. 2009). With such high accuracy and short detection periods, one second, the limitation of these systems is only in user interface design, and how many distinct targets can be presented. Other methods, such as those that use endogenous signals concerning the locus of attention, communicate at less than half the rate. (Allison et al. 2010a).

The present experiment is designed to use SSVEPs in conjunction with the endogenous parietal and occipital alpha and beta band activities associated with directed attention to track the locus of attention more precisely than is possible when using either modality alone. The experimental display uses two checkerboards that flicker at different rates. These checkerboards are intended to generate SSVEPs, even when the locus of attention lies between the two checkerboards. This lets one use EEG to estimate the locus of attention through an interpolative procedure. In addition to this SSVEP-based method, the separate alpha and beta band lateralizations associated with directed covert attention can provide convergent information when training an algorithm to predict the locus of attention.

Results indicate that the unattended, frequency-tagged stimuli in the periphery produce weak EEG signals and are not useful in tracking the locus of attention. However, results do support the notion that endogenous brain activity associated with directed attention can be used to track the horizontal position of the locus of covert attention through an examination of the degree to which alpha, beta, and gamma band power is lateralized.

Methods

Experimental Setup

Six male subjects, between the ages of 25 and 54, participated in the experiment. All subjects had normal or corrected-to-normal vision, and none reported possibly confounding neurological conditions. Subjects varied widely in their experience with EEG and visual attention experimentation. Eight to ten sessions of EEG data collection, each roughly 15 minutes in length, were performed by each subject across either two or three days. Work with human subjects was approved by the UC Irvine Institutional Review Board under protocol 2008-6342.

The experiment was conducted in an isolated room with no light except for that from the experimental display. Subjects were seated at a viewing distance of 0.76m from an LED monitor of diagonal 68.6 cm. The display was positioned at eye level and subtended 56^{o} in azimuth by 26^{o} in elevation. The display device was controlled by Matlab 2012b (Mathworks) and PsychToolBox 3.0. EEG data was collected using 10-20 configuration, 64-sensor, Waveguard EEG caps. These provided signals to an Advanced NeuroTechnologies (ANT) EEG amplifier at a rate of 256 samples per second. The output of the amplifier was controlled using ANT libraries for Matlab. During setup, all channels were measured to have impedance below 10KΩ.

The display showed a gray background, a white fixation cross, two peripheral, contrast-reversing checkerboards, and individually presented attention targets (figure 1). The gray background, the median allowed gray value in PsychToolBox, was present at all times during the experiment. The white fixation cross was located at the center of the screen and was $2°$ in width and height. Checkerboards were located at extreme right or extreme left of the display, subtended a rectangle of $[8°, 27°]$. The checkerboards were constructed of 10 squares by 30 squares, each with sides of $0.89°$. Flickering field contrast reversed at either 24 or 36 Hz, completing full cycles at 12 or 18Hz, respectively. Flickering fields were presented in two conditions: 1) 18Hz reversal at left and 12Hz reversal at right, and 2) 12Hz reversal at left and

18Hz reversal at right. Single, black letters of height $1°$ were used as attention targets. The letters used were $\{A, F, H, L\}$ and were presented in uniform-random sequence with no sequential repeats. Target positions varied horizontally. Their vertical position was held constant at the center of the display. Target horizontal position varied uniformly within the interval $-17°$ and $17°$ about the center of the display, which did not overlap the regions containing the flickering fields. Target position in any one trial lay at least 2° from the previous trials.

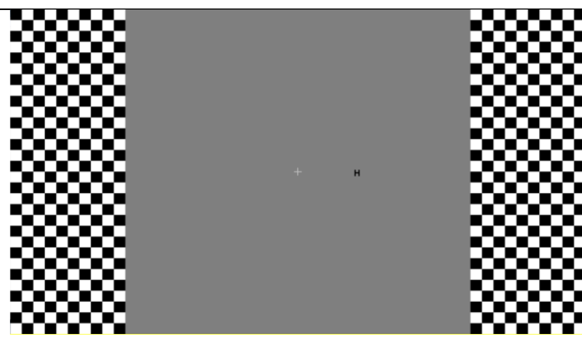

Figure 1: Experimental display
Shown is the experiment display for experiment 1. At display left and right are the flickering checkerboards stimuli. In the first condition 18Hz flicker was present at left and 12Hz flicker at right. In the second condition 12Hz flicker was present at left and 18Hz flicker was at right. At center, in white, is the fixation cross to which subjects directed their gaze during data collection. Letter H, to the right of cross, is a covert attention target for a particular trial. Targets were presented at 0° elevation and at a horizontal locations that varied between $-17°$ and $17°$ azimuth.

Subjects were instructed to hold their gaze at the central fixation cross during data collection and to avoid blinks, eye and muscle movements. Each trial presented a single attention target in a new horizontal position for 1500msec. Each trial was followed immediately by the next. Subjects were instructed to fixate on the central cross during each trial while directing attention to the target as it appeared. Subjects were further instructed to use the keyboard to indicate the identity of the target letter. A total of 420 trials were recorded for each session, and four sessions were recorded for both condition one and condition two.

Feature Extraction

Further signal processing and analysis were conducted offline in Matlab and Python. The first and last trials of each session were discarded. Trials corrupted by blinks or saccades were rejected by a method of channel time-series variance comparison. Variance of time-series from each trial was computed at each channel. The mean and variance of the channel time-series variances were computed within each session. Trials containing more than five channels with variance greater than two standard deviations from the grand mean were rejected. Using this method, between ten and thirty-seven trials were rejected from each session leaving between 383 and 410 trials per session for the four sessions from each subject. The two mastoid channels were ignored and the remaining channels were filtered between 1 and 50Hz with a digital, band-pass elliptical filter. Spectral power was estimated by Morlet wavelets at the fundamental frequency, and first harmonic frequency of the flickering fields, or 12, 18, 24 and 36 Hz.

Trial intervals of interest were identified by t-testing. Data from all subjects under both experimental conditions were included. T-testing compared all wavelet response samples, at all channels. This produced 87,544 simultaneous tests. The Bonferonni method was used to correct for multiple comparisons, and an alpha value of 0.025 was used for significance testing.

Results of testing can be seen topographically in figure 2. Significant, continuous group separation was found in parietal, occipital, and frontal electrodes at the four frequencies listed above, between 350 and 600ms after the appearance of a new attention target.

355ms **418ms** **529ms** **602ms**

a. b. c. d.

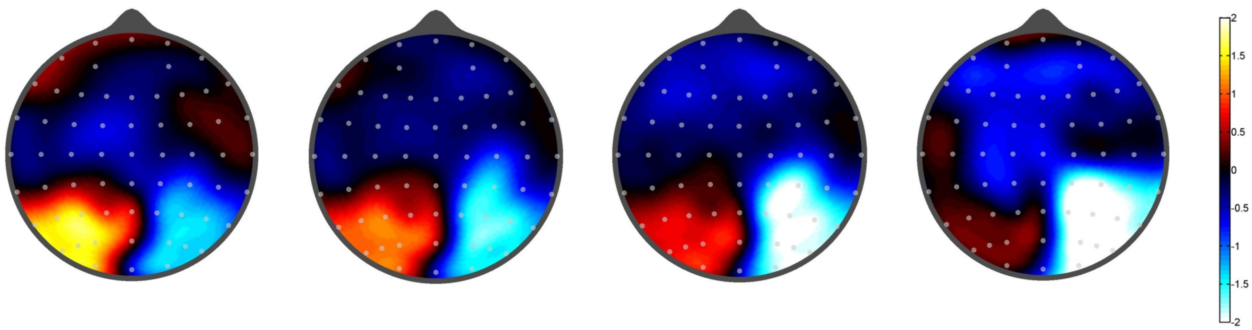

Figure 2: Feature discovery by t-testing
EEG channels that help to distinguish left *vs*. right locus of attention between 355 (leftmost topographic plot) and 602ms (right-most) after target appearance are revealed by statistical results. Displayed are normalized t-values from testing of the low-beta band (16-20Hz) at 352, 418, 527 and 602ms after target appearance. This period displayed the longest, continuous, significant group separation during the trial period. For topographic visualization, corrected t-values were normalized to display statistically significant differences when values are of t are <-1 or >1.

To generate a Common Spatial Pattern (CSP) feature set, wavelet responses at 12, 18, 24, 36Hz were integrated between 350 and 600ms post target appearance. Data processing thus resulted in 248 (4 frequency power estimates at 62 channels) CSP features per trial, which were then centered and sphered within session in preparation for tracking algorithm training and testing ($n \approx 1990, d = 248$).

Predictive modeling

Cross-validated classification was conducted with linear and nonlinear predictive models to estimate the precision and reliability by which locus of attention can be predicted in the presence of peripheral flicker. Bayes-optimal, Discriminant Analysis and Random Forests (RF) were used. Prior to cross-validation block data-splitting, outliers were removed by nearest neighbor data-prototyping using the δ-metric described by Harmeling and colleagues (2006). Discriminant analysis used a spherical Gaussian prior and shared covariance structure, yielding a linear discriminant (LDA) and regularized MAP solution. Random Forests included ensembles of 55 boosted, bagged and pruned decision trees. The optimal number of trees was chosen by cross-validation. Nine-fold cross-validation was used and classification results are reported as the empirical, binomial distribution (expected and 97.5% central density) of accurate attention location prediction. For classification of attention location, the $34.48°$ sampling space of attention targets was divided into $2, 3, 5$ or 7 equal-sized bins of $17.24°$, $11.49°$, $6.90°$ and $4.93°$ respectively (figure 3). Random Forest training included permutation feature importance to investigate spatial-spectral contribution to predictability of locus of attention. LDA solutions used for topographic visualization were fit with all post-outlier removal available data.

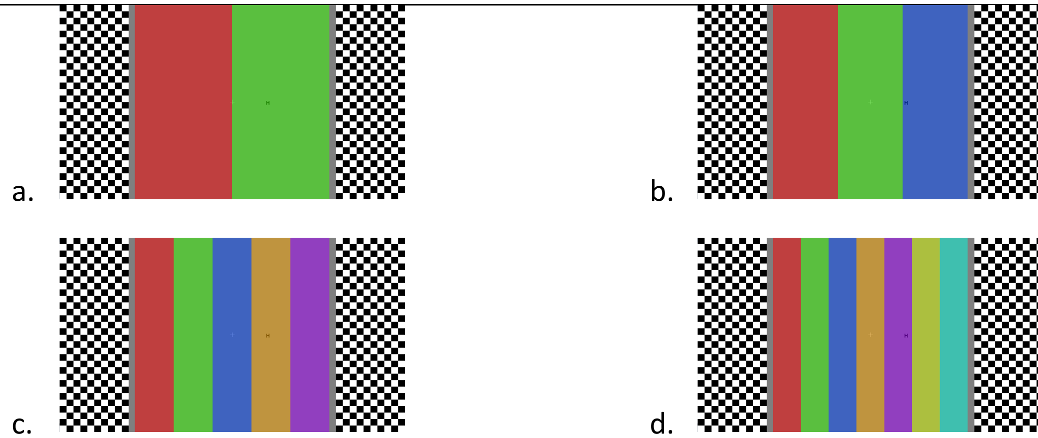

Figure 3: Binning of attention target space for n-way classification
To determine predictive accuracy at increasing precision, the attention sampling space was divided into 2, 3, 5 or 7 horizontal bins (subfigure a, b, c and d respectively).

Results

Figure 4 shows the accuracy results when predicting attention location from EEG using LDA and Random Forests. For conditions 1 and 2, locus of attention could be accurately predicted with LDA, at a rate significantly greater than chance, when the target space was divided into 2, 3, 5 or 7 bins. With the exception of two subjects, for all test conditions, the 97.5% central density of the empirically-derived, classification accuracy distribution did not overlap with the chance classification rates. Similarly, nonlinear Random Forest models yielded classification accuracy above chance, under the same conditions, though performance was systematically lower than corresponding linear models. In terms of communication rate, a maximal ITR of 14.22 BPM was found for subject 4, in the three-bin case, with an accuracy of 55%.

Condition 1 **Condition 2**

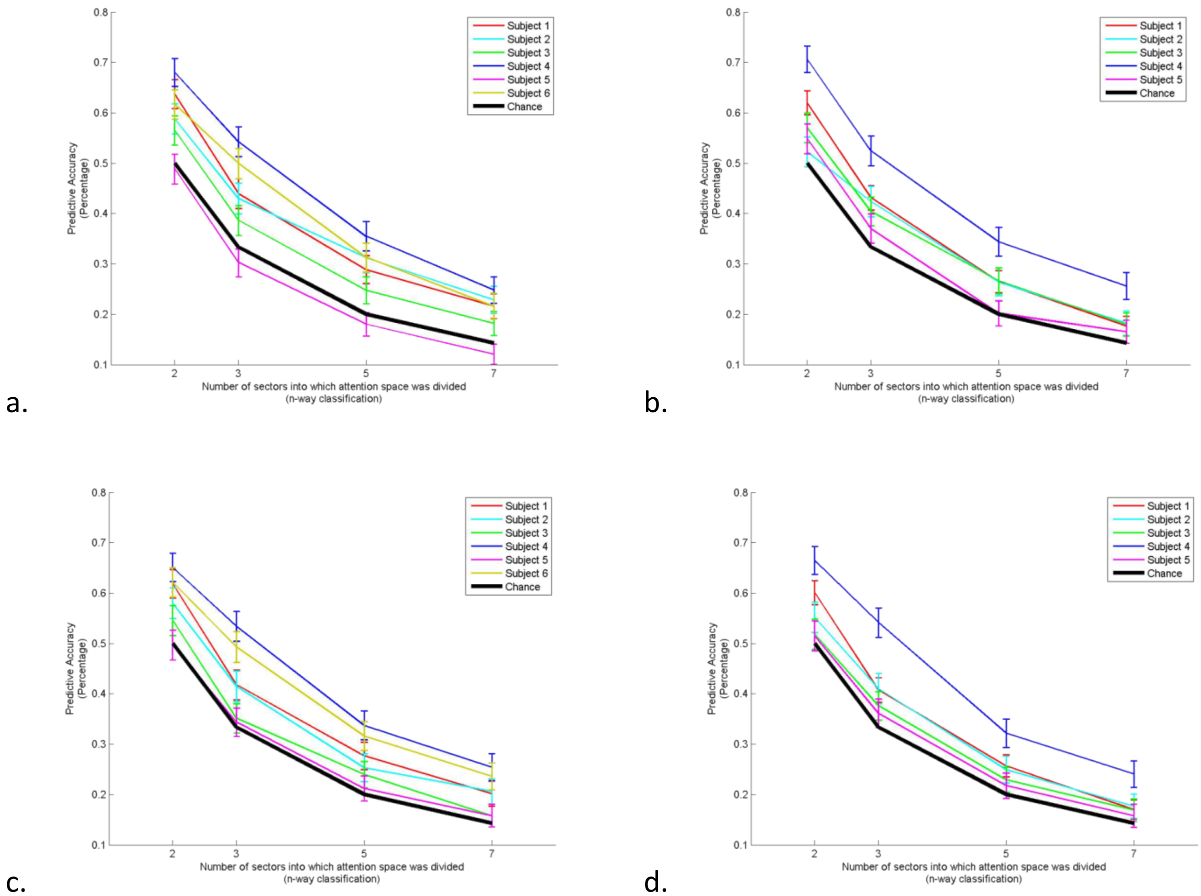

Figure 4: Attention tracking accuracy rates at increased discriminant precision
a,b: Empirical, expected predictive accuracy and 97.5% CI for LDA models as attention target sampling space is divided into more numerous and narrow bins. In bold black is the chance accuracy rate at each binning. All tracking rates can be seen to be significantly better than chance except for the rates of subject 5.
c,d: Empirical expected accuracy and 97.5% CI of Random Forest models. Performance is systematically, but not significantly, lower than that found with linear models with the exception of subject 4, condition 2 with 3 bins. Tracking performed with better than chance accuracy in all but subjects 3 and 5.

Inspection of confusion matrices from the LDA models indicates notable patterns in errors common to high and low performing subjects (figures 5 & 6). Across subjects and analysis conditions, the central-most bins were always predicted with the most accuracy, followed by extreme left and extreme right bins. Results of this type imply that the most identifiable spectral-spatial EEG features are produced when a subject's covert attention locus is either very near or very distant from the location of gaze. Furthermore, high-performing subjects display confusion matrices with block-diagonal patterns, indicating that when prediction errors are made, the incorrectly predicted bin is adjoining the true location of the subject's attention. Lower-performing subjects did not exhibit any of these patterns in their confusion matrices.

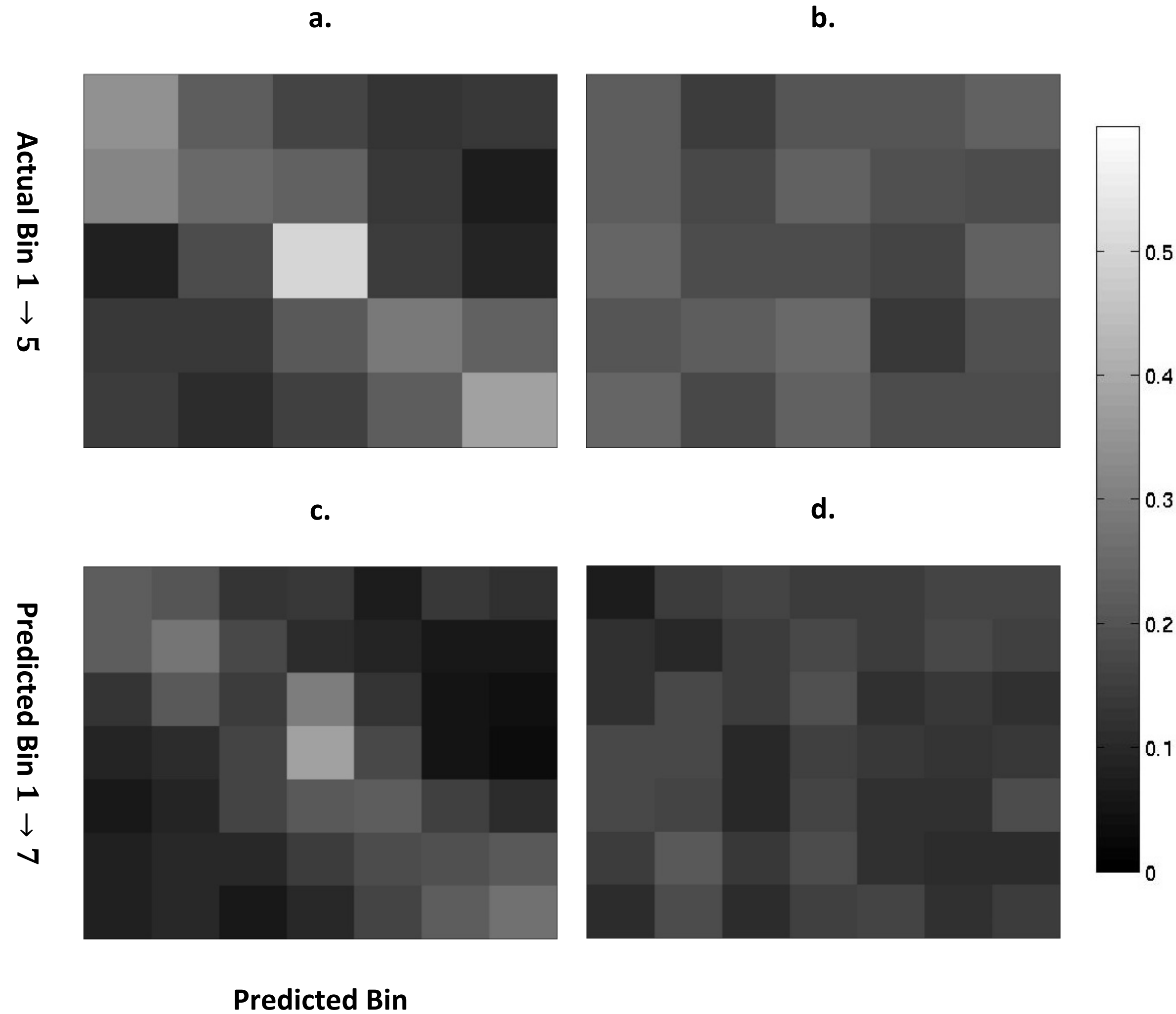

Figure 5: Confusion matrices from the best (a,c) and worst (b,d) performing subjects in condition 1
The confusion matrices of the LDA models indicate the probability of a model to predict one of the n-bins given the actual attention location in the held-out data. Actual attention location bins are ordered along the rows from top, the leftmost attention bin, to bottom, the rightmost attention bin. Error free models would display a perfectly diagonal matrix structure. Despite the LDA models not being designed with target spatial order in mind during fitting, the best performing subjects' confusion matrices display block-diagonal structure. This indicates that models fit to subjects with the highest accuracy rates most often make prediction errors into bins neighboring the correct attention location. Such a result implies shifting locus of attention and informative alpha and beta band power EEG features covary in a linearly consistent fashion in high-performing subjects.
a: The 5-bin LDA model of the best performing subject.
b: The 5-bin LDA model of the worst performing subject.
c: The 7-bin LDA model of the best performing subject.
d: The 7-bin model of the worst performing subject.

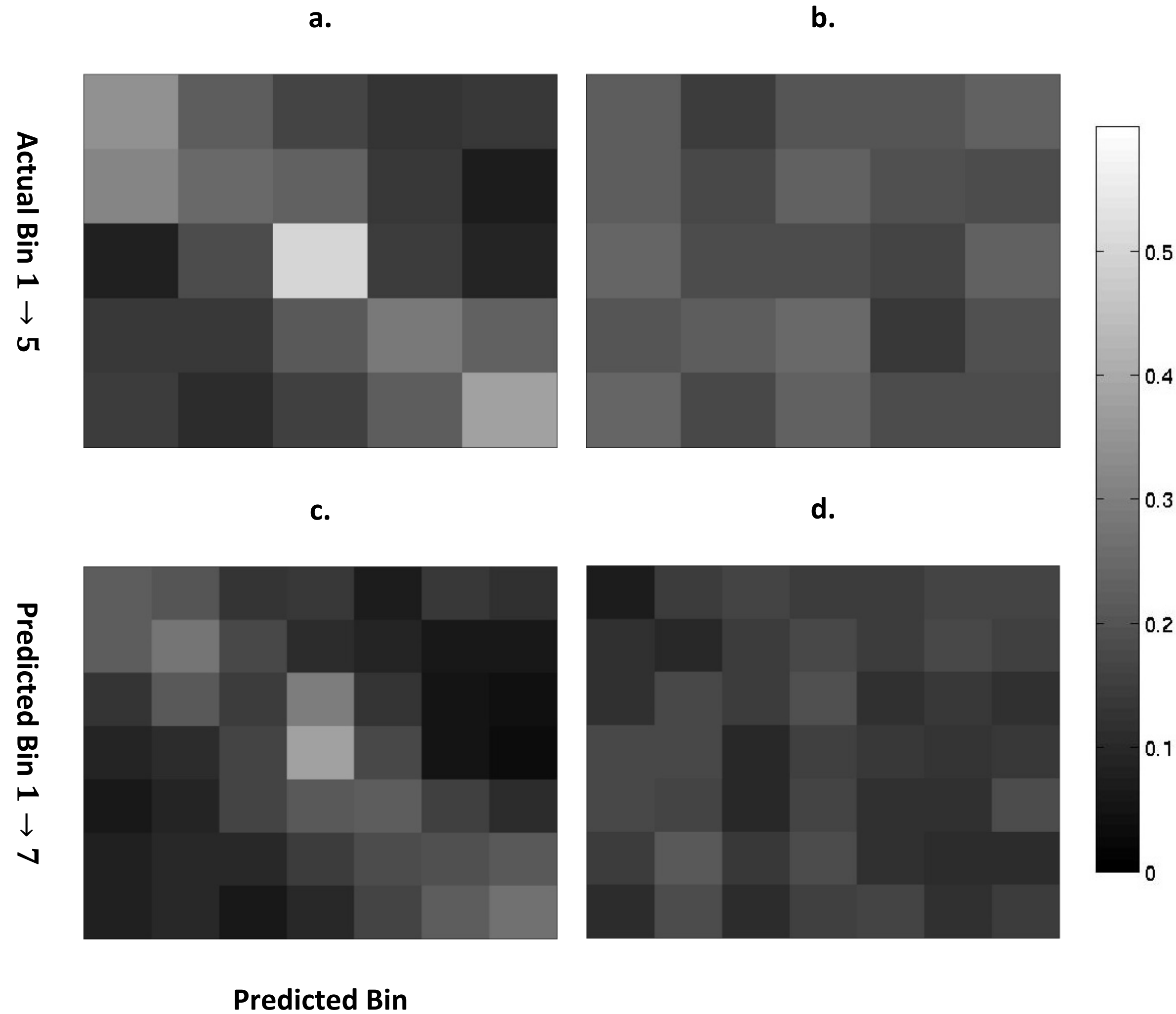

Figure 6: Confusion matrices from the best (a,c) and worst (b,d) performing subjects in condition 2
As in figure 5, models from the best performing subjects, fit under condition two also displayed block-diagonal structure, while models fit to the poorest performing subjects error structure was uniform.
a: The 5-bin LDA model of the best performing subject.
b: The 5-bin LDA model of the worst performing subject.
c: The 7-bin LDA model of the best performing subject.
d: The 7-bin model of the worst performing subject.

Figures 7 and 8 show the linear models of the best performer for conditions 1 and 2, respectively. These subjects display a relative decrease in alpha, low-beta, and gamma band synchrony in parietal, temporal, and occipital regions contralateral to location of attention (for attention-left and attention-right trials). Slight synchrony in frontal-eye-field regions can also be seen for attention-left and attention-right trials. For trials with covert attention to the central bin, near to fixation, a relative decrease in power at these bands in all of these regions can be seen. Random Forest classifier performance relied primarily upon lateral-parietal and temporal power in the alpha and low-beta bands. These activity patterns were less spatially and spectrally specific, or completely absent in the subjects with chance or near chance performance (figures 9 & 10). These spectral-spatial feature patterns preferred by good performing models are consistent with the covert visual spatial attention "orienting network" described by Posner and colleagues (2007).

Predictive performance and model coefficients were essentially the same across conditions 1 and 2. This is not consistent with the experimental hypothesis that peripheral flicker induces bottom-up SSVEP activity.

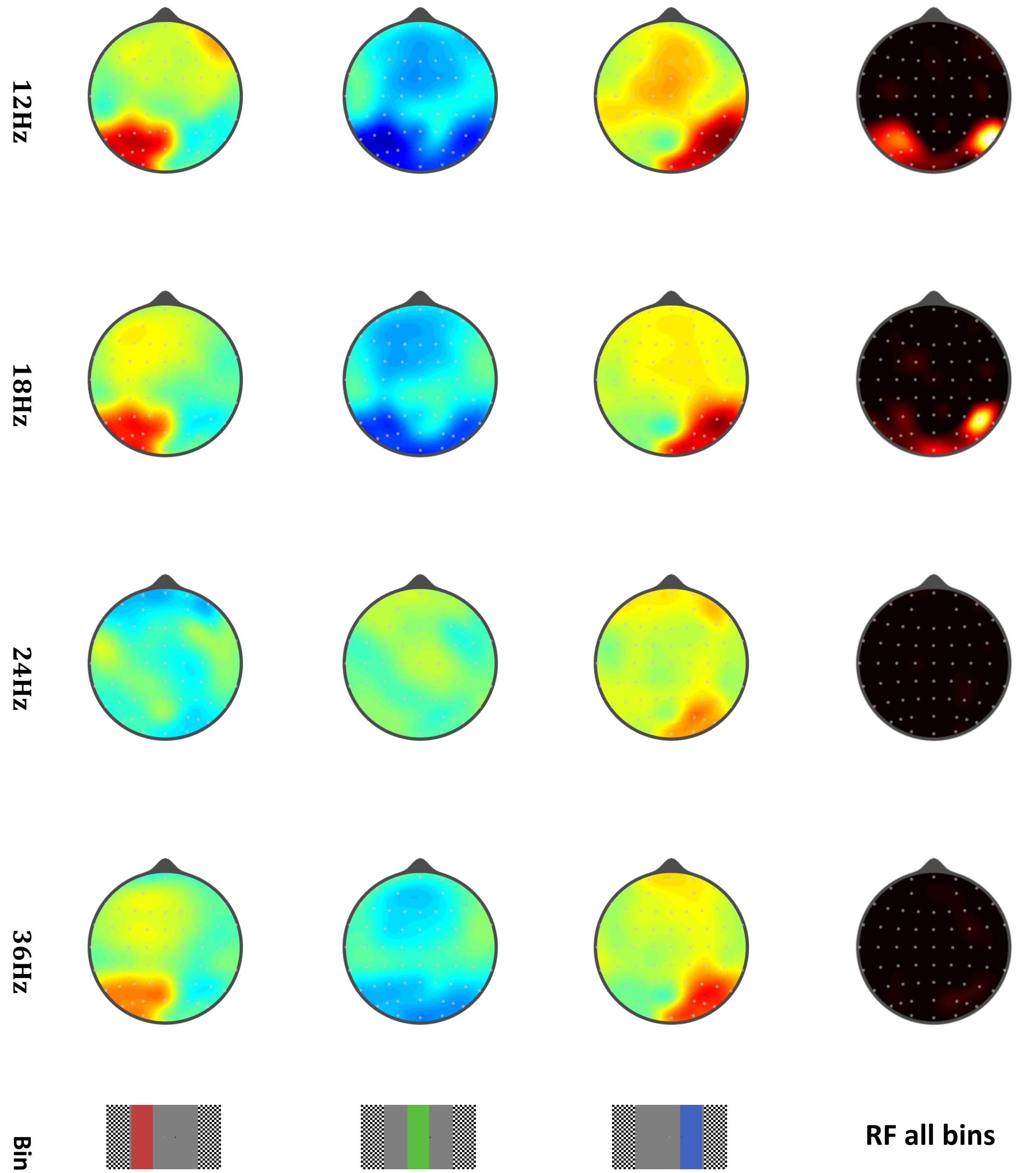

Figure 7: Models from the best performing subject in condition 1
Left: LDA model class means, contralateral desynchrony in alpha, low and high-beta and gamma bands can be seen in visual, parietal and temporal regions. Desynchrony is seen bilaterally when covert attention location is near to fixation.
Right: RF feature importance indicates performance depends primarily on features from the alpha and low-beta band in occipital and parietal-occipital-temporal junction.

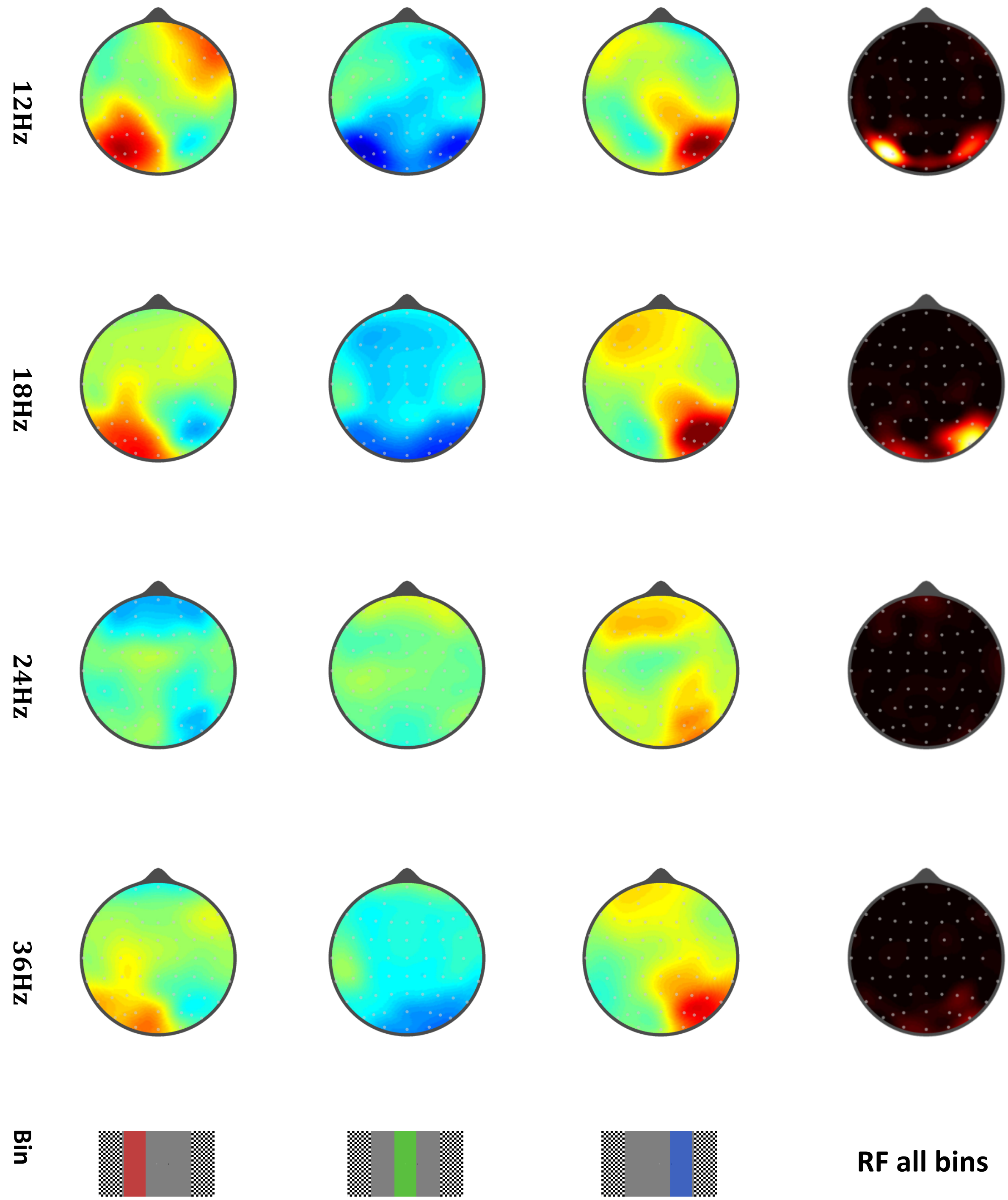

Figure 8: Models from the best performing subject in condition 2
Left: LDA model class means for subject 4, condition 2, with 3 bins. Spectral-spatial patterns are similar to those seen in condition 1. Unattended visual stimuli appear to have little effect on the EEG power at frequencies and harmonics of the stimulus flicker rate while directing attention.
Right: Alpha and low-beta activity in occipital and parietal-occipital junction contribute most to accurate tracking of attention. The change in position of the flickering fields has no effect on RF model feature importance.

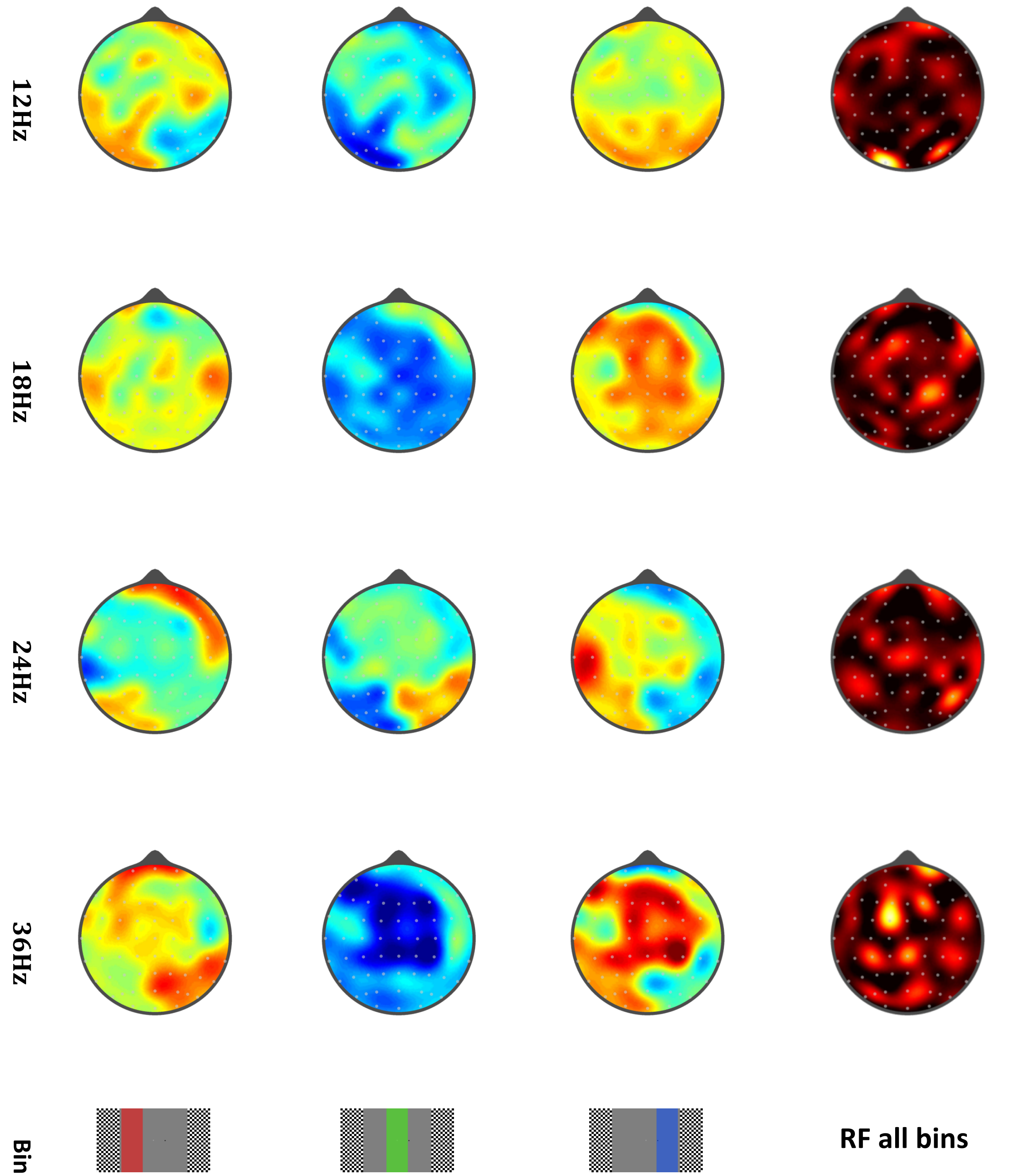

Figure 9: Models from the worst performing subject in condition 1
Left: LDA model class means for the worst performing subject, subject 5, condition 1, with 3 bins. Contralateral desynchrony prominent in high performing subjects is absent.

Right: RF Feature importance shows little spectral or spatial specificity from models

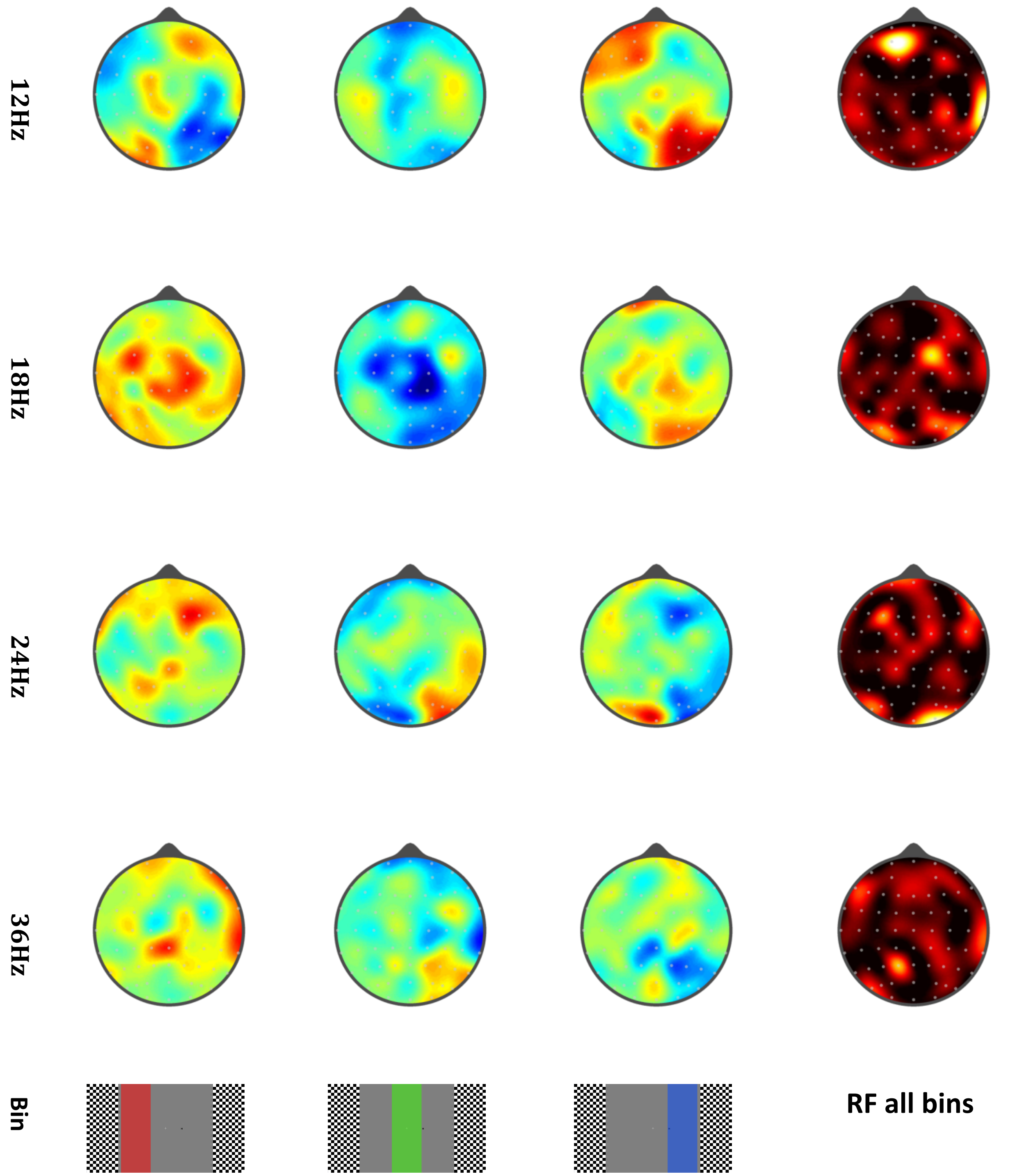

Figure 10: Models from the worst Performing subject in condition 2
Left: LDA model class means for subject 5, condition 1, with 3 bins. None of the distinct synchrony seen in high performing subjects is present.
Right: RF feature importance also shows little spectral or spatial specificity from common in models from better performing subjects.

Discussion

Peripheral flickering stimuli had no effect on either activation patterns or classification results. Despite this negative result, tracking accuracy for most subjects was still at rates significantly above chance. Classification rates, for both conditions, in the two-bin case are similar to those seen in offline and online covert visual spatial attention based EEG BCI systems (Tonin et al. 2012 & 2013). Reported accuracy in these studies was between 65 and 70% for most subjects. Detection algorithms in these previous studies utilize a time-dependent, integrated evidence method and work with features from the alpha band only. The CSP approach presented here uses multiple canonical frequency bands and performs comparably offline. Previous studies direct a subject's attention to one of two specific attention locations, either to left or to right, in anticipation of an oncoming target, and analyze the ISI period. This covert visual spatial attention method not only tracks attention over the continuous visual field, but does so when attention is actively engaged; a more natural behavior. Further significant predictive performance in the three through seven bin cases is a new result.

Regions implicated in predictive modeling are consistent with previous covert visual spatial attention EEG studies (Rihs et al 2007, Thorpe et al. 2012, and Sauseng et al. 2005), MEG (Bahramisharif et al. 2010 and Gerven et al. 2009) and fMRI studies (Silver 2005). These include frontal-eye-field (FEF), occipital and parietal cortex, specifically intraparietal sulcus (IPS). Directing covert attention away from the center of gaze is associated with marked desynchrony in contralateral parietal regions, perhaps caused by increased non-synchronous activity in these regions. Directing covert visual spatial attention towards gaze location is more associated with desynchrony in parietal lobes of both hemispheres. Parallel activity in both parietal lobes was also reported by Silver (Silver 2005). Novel to these results are the patterns of activity in low-beta and gamma bands in the above-mentioned regions. Previous studies focus on variations of activity only in the alpha band. Results from this study indicate that low-beta is equally important when tracking locus of covert visual spatial attention.

The null-effect of peripheral, unattended flicker on either classification or model fitting results could be the explained in one of two ways: 1) the flicker introduces symmetric noise into regions and EEG bands useful in tracking covert visual spatial attention or 2) the attention system effectively suppresses these very conspicuous, unattended stimuli. This could be solved by repeating this experiment without flicker, and comparing prediction rates. If prediction rates are comparable, and potentially influential stimuli such as these are effectively suppressed as far as this attention tracking method is concerned, then it is plausible that tracking covert visual spatial attention could be performed as effectively in a much more visually-rich scene. This would motivate further research using this attention tracking method in a real world or virtual environment.

III. Tracking attention in one dimension using EEG

Introduction

EEG BCIs using endogenous brain signals resulting from directed attention have several advantages over ERP based methods. First is that there is no need to display extraneous visual stimuli in order to evoke SSVEPs. A second is that a method that can passively track the locus of attention is likely to be more natural and intuitive to the user.

The results from the first experiment indicate that it is feasible to track attention using CSP features generated from canonical EEG power-bands. Furthermore, using these features, attention locus can be tracked in up to seven distinct bins of horizontal visual space. The present experiment and the experiment to be described in the next chapter were then devised to further investigate this finding by conducting experiments similar to experiment one, but with the flickering fields removed.

The aim of the present study was to infer EEG power-band features associated with changes in position of attention locus along azimuth and along elevation. In addition, predictive modeling was used to determine the spatial precision with which visual attention can be tracked using informative EEG features. Results showed that endogenous EEG power-band features can be used to track visual attention horizontally or vertically. Furthermore, attention can be tracked with greater spatial precision than has yet been reported.

Methods

The EEG experiment consisted of two conditions, one where the subject's locus of attention location varied in the horizontal direction only and one where the subject's locus of attention varied in the vertical direction only. Informative EEG power-band features were then detected by t-testing. Linear and nonlinear classification methods were then applied to evaluate the feasibility of attention tracking.

11 subjects (ten male and one female, age range 21-54) participated in the experiment. All subjects had normal or corrected-to-normal vision, and none reported possibly confounding neurological conditions. Subjects varied widely in their experience with EEG and visual attention experimentation. Twenty sessions of EEG data collection, each roughly fifteen minutes in length, were performed by each subject across either two or three days. Work with human subjects was approved by the UC Irvine Institutional Review Board under protocol 2008-6342.

The experiment was conducted in an isolated room with no light except for that from the experimental display. Subjects were seated at a viewing distance of 0.76 from an LED monitor of diagonal 68.6 cm. The display was positioned at eye level and subtended 56^{o} azimuth by 26^{o} elevation and was controlled by Matlab 2012b (Mathworks) and PsychToolBox 3.0. EEG data was collected using gelled electrode, international 10-20 configuration, 64-sensor Waveguard EEG caps. These provided signals to an Advanced NeuroTechnologies (ANT) EEG amplifier at a rate of 256 samples per second. The output of the amplifier was controlled using

ANT libraries for Matlab. During setup, all channels were measured to have impedance below 10KΩ.

The experimental display showed a gray background, a white fixation cross, and individually-presented attention targets in the form of black letters. The white fixation cross was located in the center of the experimental display and subtended 2^{o} of visual angle. The letters used as attention targets were 1^{o} of visual angle in height and were uniformly sampled from the set {A,F,H,L}.

The experiment had two conditions. In the first condition, attention targets were presented at 0^{o} of elevation and varied in horizontal position between -17^{o} (left) and 17^{o} (right). In the second condition, attention targets were presented at 0^{o} of azimuth and varied vertically in position between -17^{o} (down) and 17^{o} (up). Sequential target positions were a minimum of 2^{o} of visual angle from the preceding target and target letters did not repeat.

Subjects were instructed to hold their gaze at the central fixation cross during data collection and to avoid blinks, saccades and other muscle movements. Each trial presented a single attention target in a new position for 1500msec, and was followed immediately by the next trial. While maintaining fixation, subjects directed their attention towards the newly-presented target, maintained attention upon the target, and responded with a key-press indicating the identity of the letter. A total of 420 trials were recorded for each session. Up to ten sessions were collected on a given day. Each session consisted of only one experimental condition. The session type was randomized and four sessions of data were conducted for conditions one (horizontal) and two (vertical).

Feature Discovery

Orienting visual attention to the left or right of fixation is known to be associated with lateralized changes in alpha, beta and gamma band EEG activity (Bahramisharif *et al*. 2010 & 2011, Thorpe *et al*. 2012). Results from experiment one corroborated these findings. However, a data-driven approach to discovering features useful for tracking attention was used for this experiment. This was done to both reaffirm the importance of these attention-associated features, in this dataset, and to discover any new, informative EEG power band features useful in tracking the locus of attention.

EEG data were normalized by average reference by the amplifier during recording. Further signal processing and analysis were conducted offline using Matlab and Python. The first and last trials of each session were discarded outright. Trials corrupted by blinks, saccades or other muscle artifact were rejected by a method of channel time-series variance comparison. The variance of EEG channel's time-series was computed for each trial. The mean and standard deviation of channel time-series variances were then computed within each session. Trials containing five or more channel variances greater than two standard deviations from the grand variance mean were then rejected from further analysis. This method rejected anywhere from eight to thirty-five trials per session. The two mastoid channels were then removed from the dataset. The remaining channels were filtered between 1 and 50Hz with a digital, band-pass elliptical filter. Spectral power was estimated in a time-varying fashion using Morlet wavelets

(Schiff 1994) centered at 4, 6, 10, 18, 24 and 36 Hz each within the delta, theta, alpha, low-beta, high-beta and gamma bands, respectively, and was then down-sampled by a factor of four.

Power-band feature discovery was conducted by massive t-testing of spectral power data from all subjects in either the horizontal and vertical conditions. For the horizontal condition, groups for t-testing were defined as trials in which attention was directed to either the left or the right of fixation. For vertical condition, groups were defined as trials where attention was directed above or below fixation. T-testing compared all wavelet response samples, at all channels. This produced 131316 simultaneous tests. The Bonferonni method was used to correct for multiple comparisons, and an alpha value of 0.025 was used for significance testing. Results of testing can be seen topographically in figure 11 and 12. Continuous, significant group differences were found in alpha, low-beta, high-beta and gamma band of the parietal and occipital regions between 350 and 600ms after the appearance of attention targets. These spatial and spectral features match well those described in experiment one and published studies (Bahramisharif *et al*. 2011, Cosmelli *et al*. 2011, Thorpe *et al*. 2012).

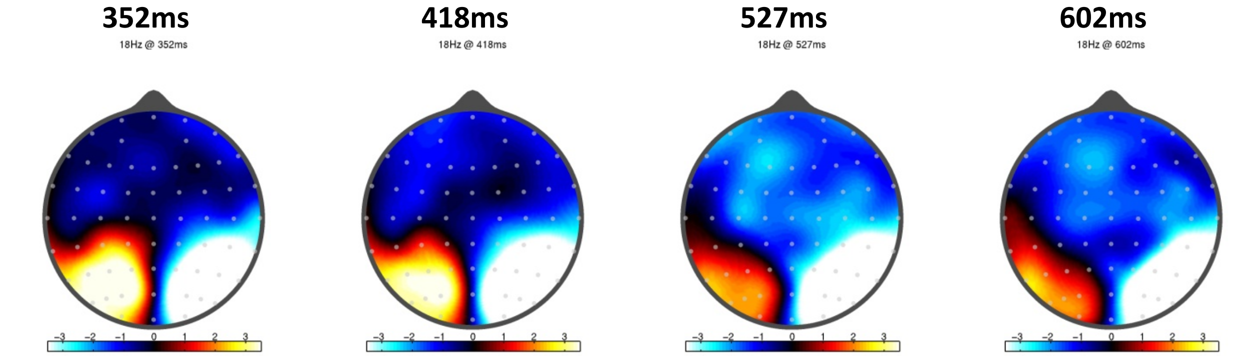

Figure 11: Feature discovery by t-testing, horizontal condition
The maximal differences between directing covert attention to the left *vs.* to the right was found in EEG alpha, low-beta, high-beta and gamma band power over parietal and occipital regions roughly between 350 and 600ms after attention target appearance. This interval was found empirically by Bonferonni-corrected t-testing, in the two-binned (figure 13), horizontal condition data from all subjects. Trial periods prior to and after this interval displayed only sporadic significant differences. Features used for predictive analysis were extracted from these EEG power bands during this time period. Displayed are normalized t-values from testing of the low-beta band (16-20Hz) at 352, 418, 527 and 602ms after target appearance. For topographic visualization, corrected t-values were normalized to display statistically significant differences when values are of t are <-1 or >1.

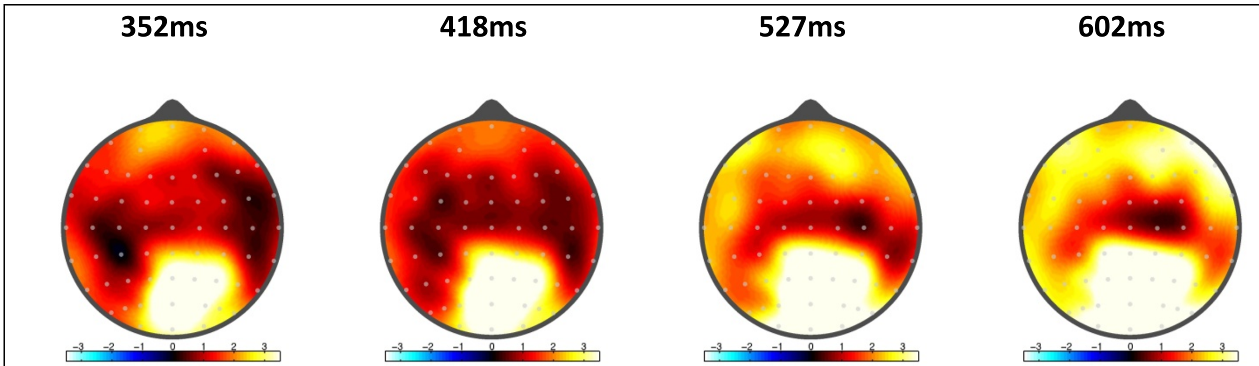

Figure 12: Feature discovery by t-testing, vertical condition
Displayed are the t-testing results of the low-beta band for the vertical condition using a two-way binning of the vertical attention location sample space (figure 13). The comparison was made between time-varying low-beta power when attention was directed above fixation minus the time-varying low-beta power when attention was directed below fixation. Red values indicate more low-beta EEG power when attending upward, while blue values indicate more low-beta EEG power when attending downward. Like in figure 3, corrected t-values were normalized to display statistically significant differences when values are of t are <-1 and >1.

Further analysis was restricted to data from the interval [350,600] msec concerning the power in the informative bands alpha, low-beta, high-beta and gamma. To generate a Common

Spatial Pattern (CSP) feature set, wavelet responses in the alpha, low-beta, high-beta and gamma bands were integrated between 350 and 600msec post target appearance. Data processing thus resulted in a 248 (4 frequency power estimates at 62 channels) CSP features per trial, which were centered and sphered within session in preparation for tracking algorithm training and testing (n = 1532+ for horizontal and vertical condition and n = 4596+ for the two dimensional condition, d = 248).

Predictive Modeling

To estimate the precision and reliability with which the locus of attention can be tracked, predictive modeling was conducted with linear and nonlinear classifiers. Linear Bayes-optimal Discriminant Analysis and Random Forest models, were chosen, as in experiment one. Outliers were removed by nearest neighbor data-prototyping using the δ-metric described by Harmeling and colleagues (2006). Discriminant analysis used a spherical Gaussian prior and shared covariance structure yielding a regularized MAP solution and linear class boundaries. Random Forests included ensembles of 55 boosted, bagged and pruned decision trees. Optimal numbers of trees were established using subsets of training data during cross-validation. Nine-fold cross-validation was used and classification results are reported as the empirical, binomial distribution (expected and 97.5% central density) of accurate attention location prediction. For prediction of attention location in either the horizontal or the vertical condition, the 34^{o} sampling space of attention targets was divided into two, three, five or seven equal-sized bins of 17.24°, 11.49°, 6.90° and 4.93°, respectively (figure 13). LDA solutions used for topographic visualization were fit with all data after cross-validated testing was complete. During cross-validation testing, Random Forest training included recording of permutation feature importance to investigate spatial-spectral feature contribution to predictability of locus of attention. Confusion matrices were computed during cross-validation testing to visualize the distribution of correct and incorrect predictions in the test data.

Communication speed was computed using ITR, a measure using the probability of successful communication of a message, the time taken to pass the message and the number of discrete messages. ITR is computed as

$$ITR = \left(\log_2 n + p * \log_2 p + (1-p) * \log_2 \frac{(1-p)}{(n-1)}\right) * \frac{1}{t},$$

where the units of ITR is *bits-per-minute* (BPM), *n* is the number of different messages, *p* is the probability of successfully passing the message, and *t* is the time in minutes to pass the message. For this experiment, *n* was the variable number of bins into which the attention sampling space was divided, and p was the empirical, expected rate of successful tracking. The CSPs used required 600msec, or 0.01 min., of EEG data to generate features while trained models would require an insignificant amount of time to make a decision. Therefore, 0.01 min. was used as *t* to compute ITR.

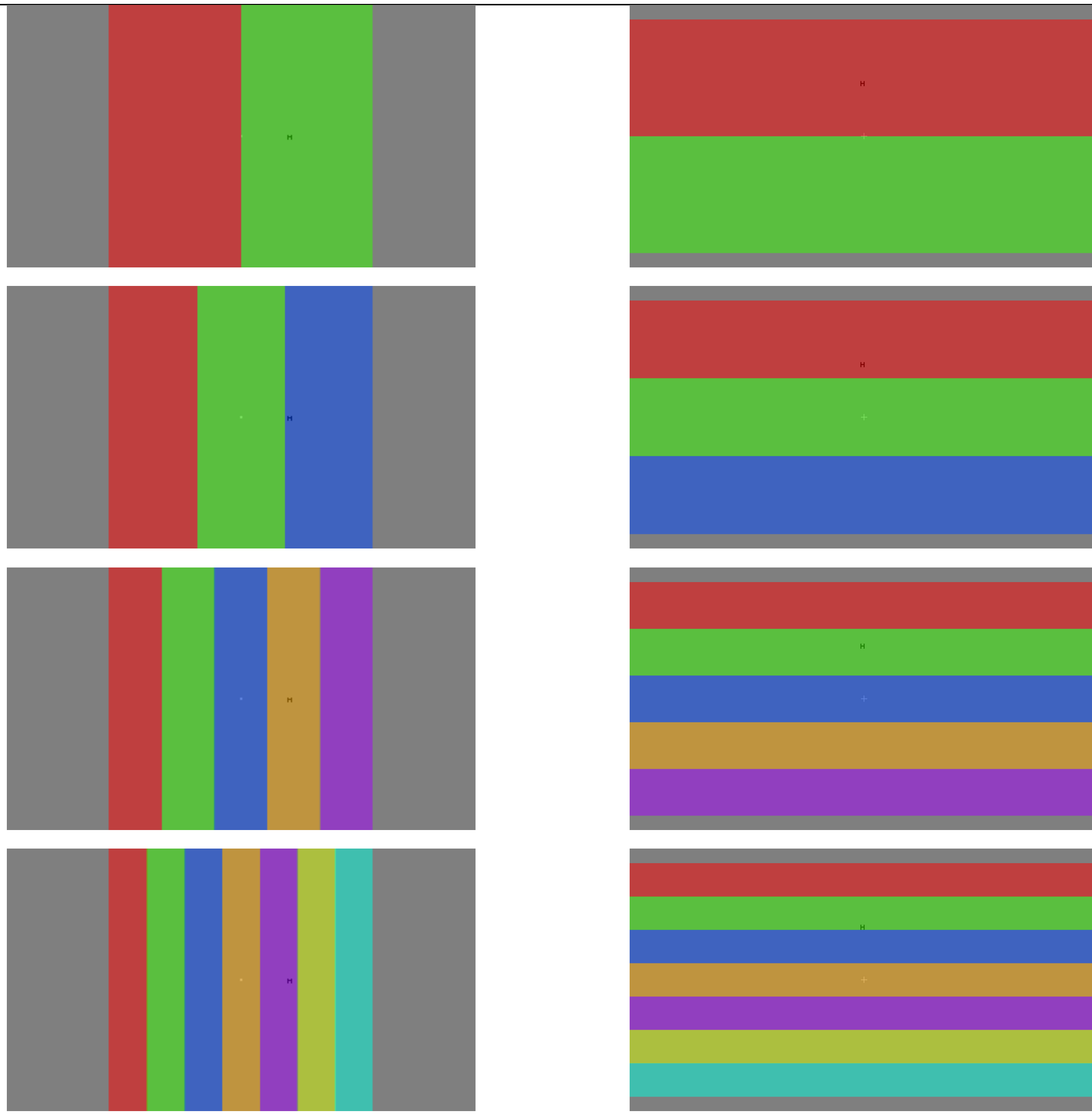

Figure 13: Binning of attention target space for n-way classification
The experiment display is shown with several overlays indicating the spatial binnings used for tracking. The experiment environment consisted of a gray background, a white fixation cross and individually presented attention targets. Attention targets took the form of black letters (the letter H in this figure).
Left: Binning of horizontally varying attention targets from two to seven bins
Right: Binning of vertically varying attention targets from two to seven bins

Results

Horizontal Tracking

Tracking of the locus of attention from EEG data was successful in almost all cases. Results when tracking horizontally varying attention into two, three, five and seven bins can be seen in figure 14. These results show that the locus of attention could be predicted at a rate significantly above chance for nine of the 11 subjects. Put more precisely, the 0.0125% experimental lower-bound binomial posterior probability of successful classification was above chance in these nine subjects. Furthermore, in five of the 11 subjects, the posterior success lower bound was at least 15% better than chance in two-way to seven-way classification. The best-performing subjects displayed expected accuracies of 68.0% in two-way, 51.1% in three-way, 30.5% in five-way and 24.2% in seven-way classifications as compared to chance accuracy rates of 50.0%, 33.3%, 25.0% and 14.3%, respectively. Regularized linear models generally performed better than nonlinear models. Though this difference was consistent across subjects and granularities of tracking, the posterior probabilities of success did not diverge in a statistically significant fashion.

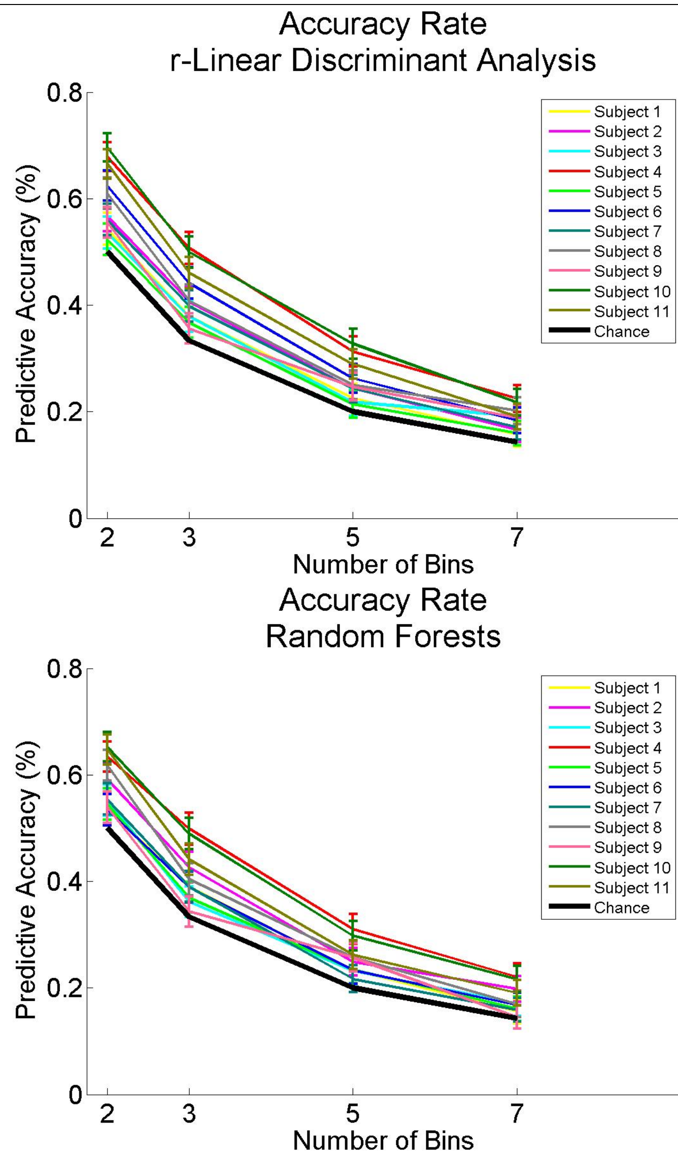

Figure 14: Tracking accuracy rates from the horizontal condition at increased discriminant precision
Empirical, expected predictive accuracy and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the horizontal attention location was tracked with greater granularity (binning shown in figure 13). Chance accuracy at each number of bins displayed as the bold, black line. All but a few subjects performed significantly better than chance up to and including 7 horizontal bins. Linear models, in most cases, performed better than nonlinear models.

The communication speed and the empirical 97.5% central density resulting from horizontal tracking using linear and nonlinear models can be seen in figure 15. In many cases the high tracking accuracy rate of the two-bin case produces the highest expected ITR. The highest ITR seen in this experiment is, in fact, the two-bin case for subject 10, which is 11.35 BPM. However, there are several subjects with maximal ITR in the three bin case. In these cases, the reduced tracking accuracy is offset by the increased number of target bins among which discrimination is being made.

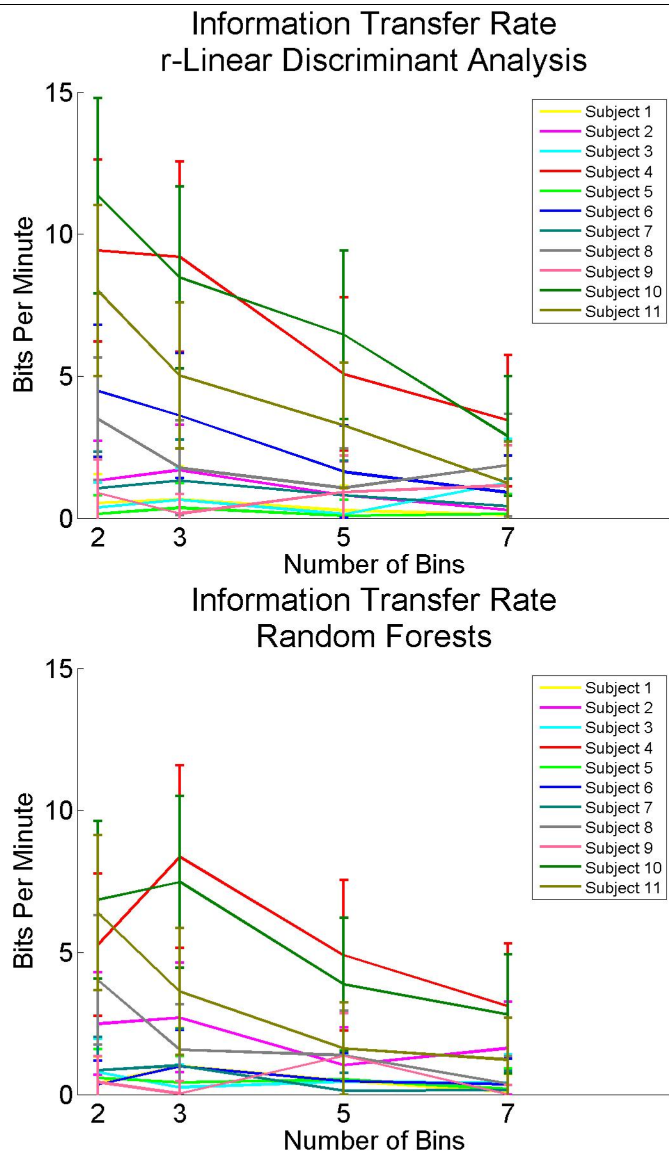

Figure 15: ITRs from the horizontal condition at increased discriminant precision
Empirical, expected ITRs and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the horizontal attention target sample space was divided into more numerous and narrow bins (as shown in figure 1). The maximal ITR is seen for subject 10 in the two-bin case, where only hemifield of attention is being detected. However, for several other subjects the three-bin case yields the highest ITR. ITR is greater in these cases because the reduction in classification accuracy is offset by the greater number of horizontal spatial bins among which attention locus is being discriminated.

The models of the best-performing and worst-performing subjects, when tracking attention into three horizontal bins, are displayed in figures 16 and 17, respectively. Linear model class means show that relatively more ipsilateral and less contralateral alpha, low-beta and high-beta power is seen in parietal and occipital regions when attention is directed to the left or right. When attention is directed near fixation, relatively less EEG power is seen in these bands bilaterally in parietal and occipital regions. Less dramatic differences in gamma band power are seen over the entire head. Random Forest feature importance indicates that alpha, low-beta and high-beta parietal and occipital features contributing most to correct tracking. These patterns of spatial power-band activity were common amongst all good performing subjects, while poorer performing subjects did not display these concentrated differences in activity (figure 17).

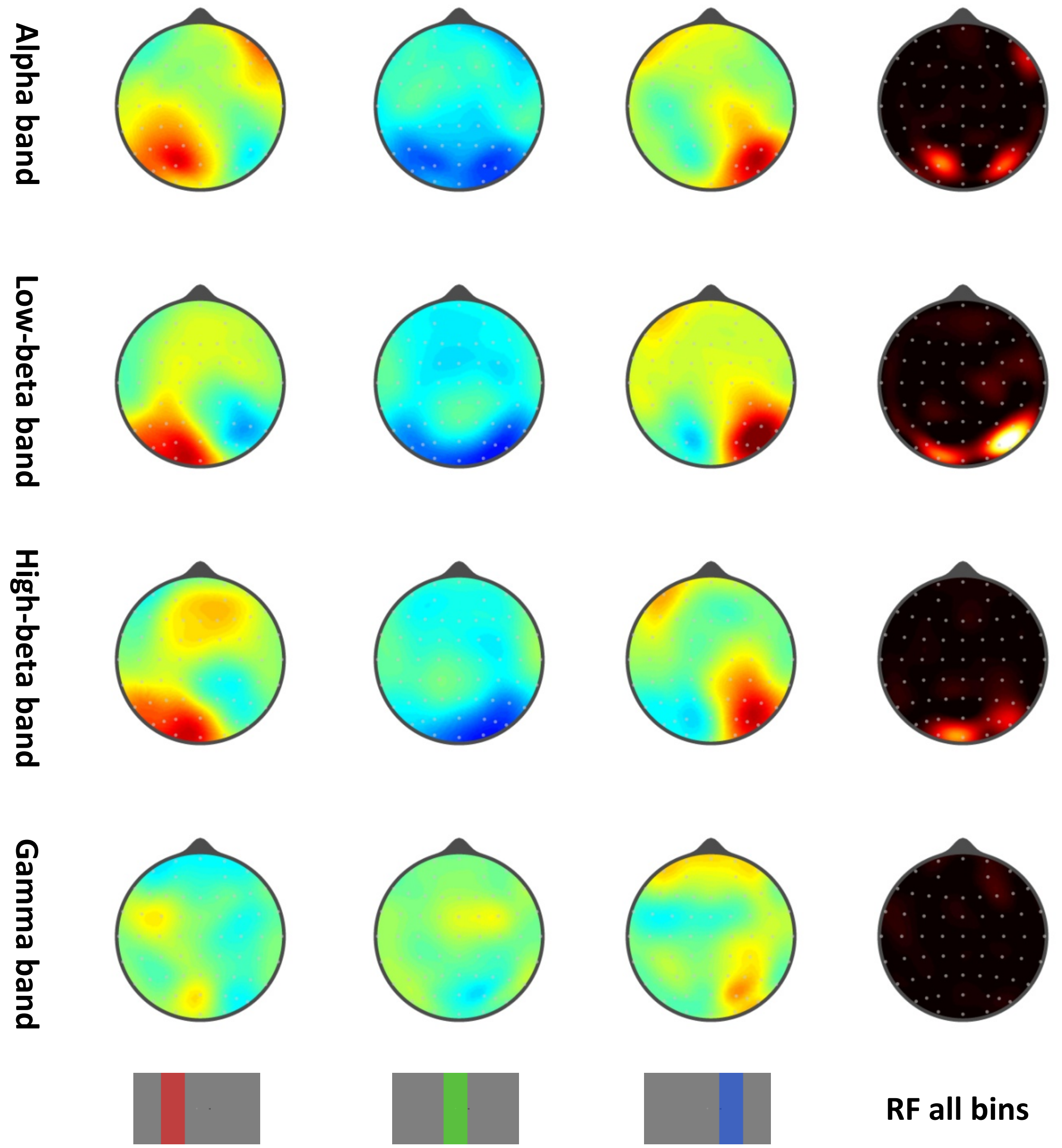

Figure 16: Models from the best-performing subject (10) in the horizontal condition
Left: LDA model class means for the 3 bin case. Class means are, from left to right, attention left, attention ahead and attention right. Increased synchrony can be seen in red while desynchrony can be seen in blue. Attention directed to the left or right is associated with increased synchrony ipsilaterally and desynchrony contralaterally in alpha, low-beta and high-beta bands of parietal and occipital cortical regions. Attention directed near fixation is associated with desynchrony in both hemispheres. These results are typical of high performing subjects.
Right: RF feature importance indicates that predictive performance depends primarily on features from the alpha, low-beta and high-beta bands. These features correspond to the notable synchrony and desynchrony in the LDA models.

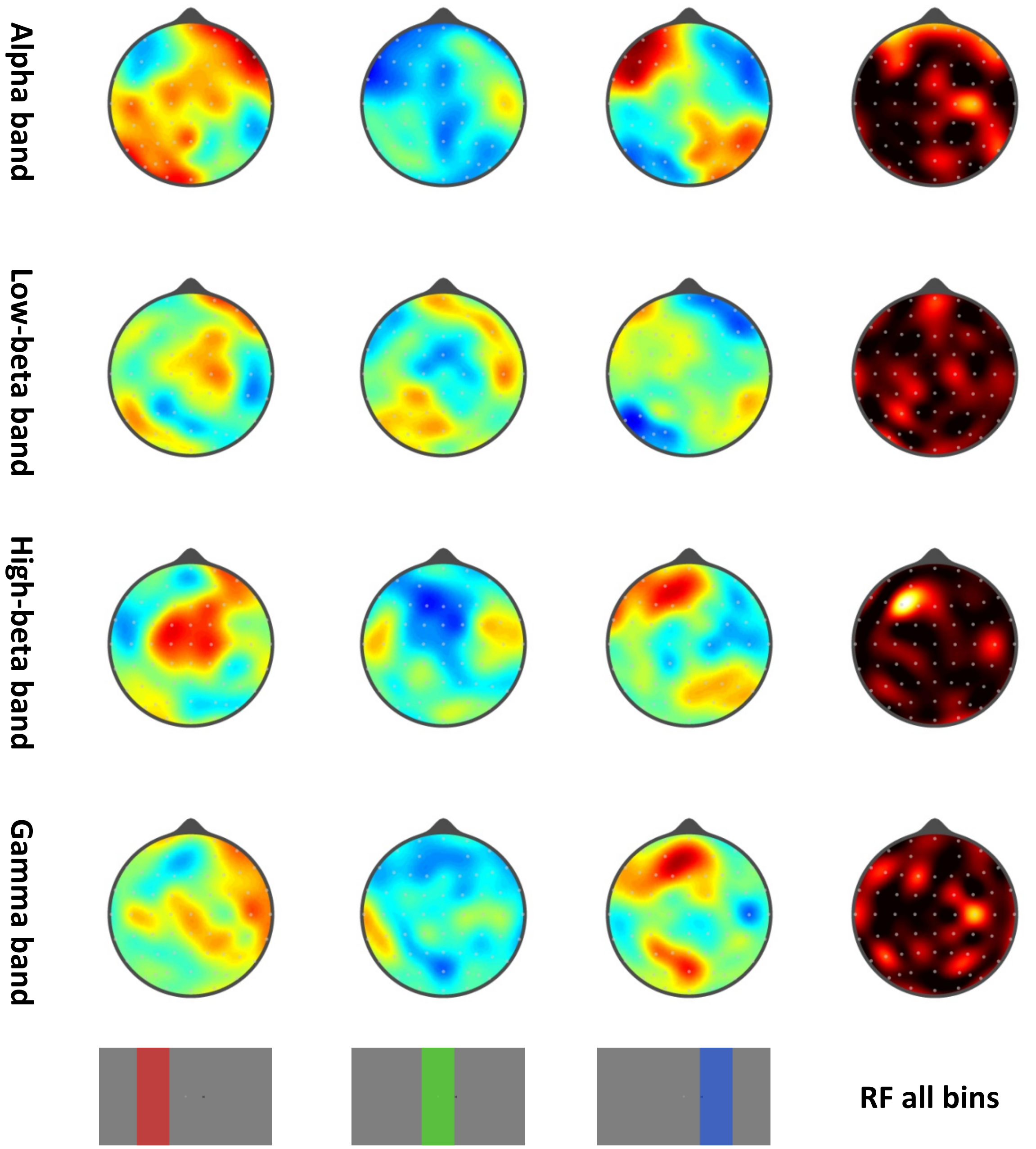

Figure 17: Models from the worst-performing subject (5) in the horizontal condition
Models fit to data from subjects with poorer predictive performance do not display the characteristic ipsilateral synchrony and contralateral desynchrony associated with horizontally directed covert visual attention.

Confusion matrices of the best-performing subjects displayed a near-block-diagonal structure (figure 18). Rows of the confusion matrices indicate the true attention location, from top row to bottom row ordered from attention left to attention right. The entries along the columns indicate the probability of predicting any attention location bin given the true location of attention. Perfect classification upon testing data would display pure diagonal matrices, with all probabilities of prediction of a particular attention location into the correct bin. The near-block-diagonal structure of the matrices indicates that when the models are making incorrect predictions, they are most often predicting into a bin neighboring the correct bin. This result was serendipitous as the proximity of the attention bins was not built into model optimization. Such a result indicates that informative EEG power at parietal and occipital head locations covaried systematically with the spatial location of covert attention. This pattern within the covariance matrices was common to all good performing subjects while poorer performing subjects displayed relatively uniform errors (figure 19).

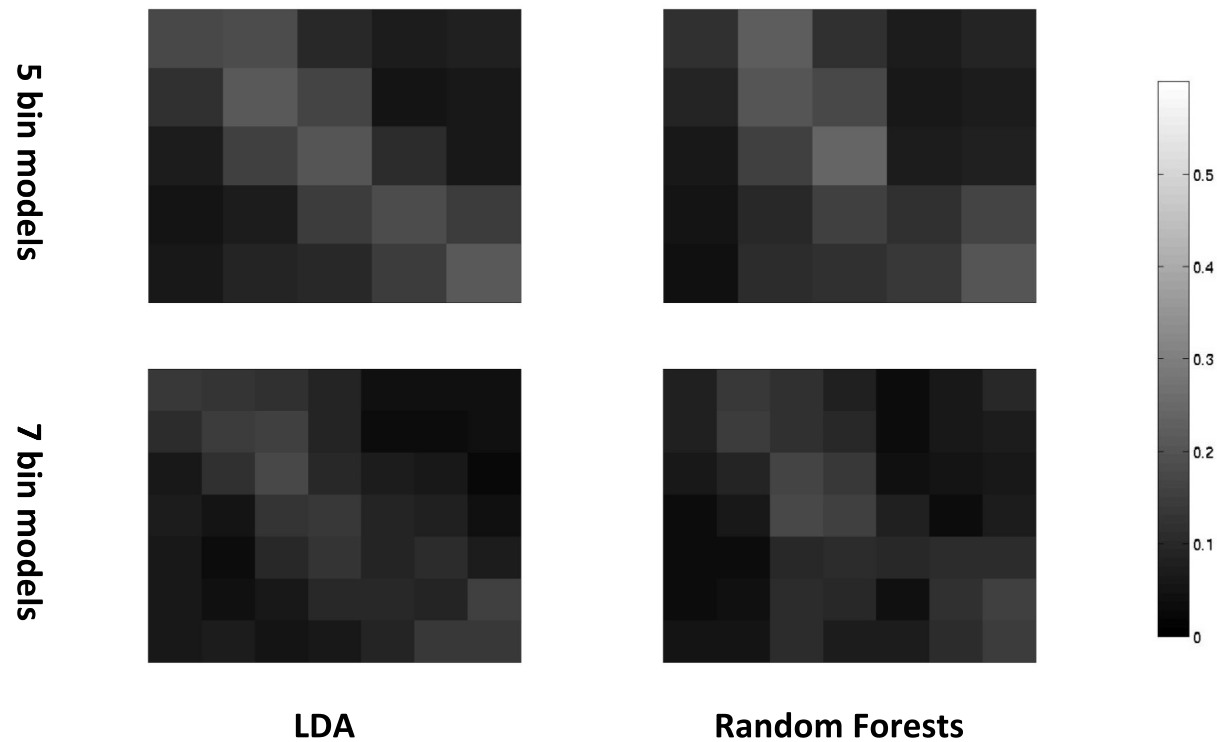

Figure 18: Confusion matrices from the best-performing subject (10) in the horizontal condition
The confusion matrices indicate the probability of a model to predict one of the n-bins given the actual attention location in the held-out test data. The actual attention location bins are ordered along the rows from top, the left most attention bin, to bottom, the right most attention bin, while probability of predicting a given bin along the columns from left most bin to right most bin. Error free models would display perfect diagonal matrix structure. Despite neither the LDA nor Random Forest having the attention bin location ordinarily built into their model fitting, the best-performing subject's confusion matrices display block-diagonal structure. This indicates that well fit models of good performers most often make prediction errors into bins neighboring the correct attention location. Such a result implies shifting locus of attention and occipito-parietal alpha and beta power covary in a linearly consistent fashion in high performing subjects.

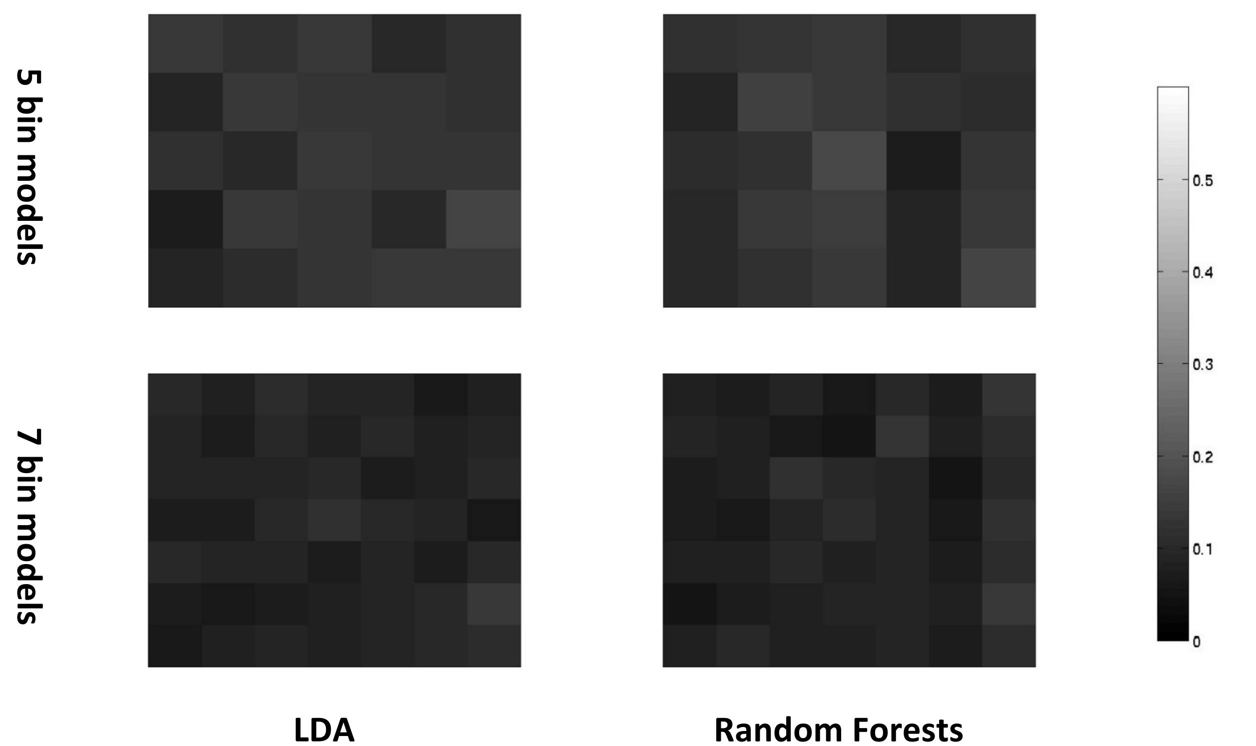

Figure 19: Confusion matrices of the worst-performing subject in the horizontal condition
Confusion matrices of poorer performing subjects display uniform distributions of probability to predict attention locations given an actual attention location.

Vertical Tracking

Tracking of attention was successful overall when attention varied in the vertical direction. However, accuracy rates are systematically lower than in the horizontal tracking case. All but three of the subjects attention could be tracked at a rate significantly greater than chance at all degrees of granularity, while three of the 11 subjects posterior predictive accuracy rates were at least 15% greater than chance at all granularities. The best-performing subjects expected accuracy rates were 61.6%, 46.1%, 30.3% and 20.8% when predicting into two, three, five or seven bins, respectively. Again, linear models generally performed better though the difference was even less dramatic than in the horizontal case.

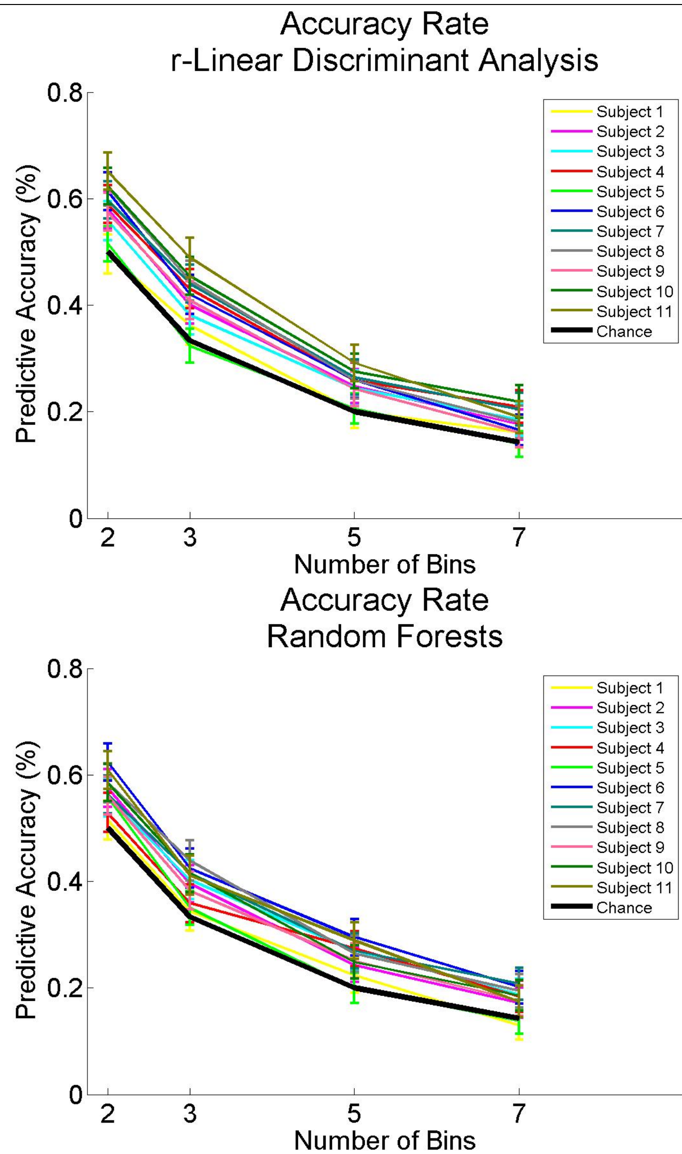

Figure 20: Tracking accuracy rates from the vertical condition at increased discriminant precision
Empirical, expected predictive accuracy and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the vertical attention target sample space was divided into more numerous and narrow bins (as shown in figure 13). Chance accuracy at each number of bins displayed as the bold, black line. All but a few subjects performed significantly better than chance up to and including 7 vertical bins. Linear Models, on average, performed better than nonlinear models.

Maximal communication speed was seen in the three-bin case for many subjects. The highest overall ITR of 7.42 was found in the three-bin case of subject 11. ITR, like tracking accuracy, was lower than that found while tracking horizontally varying attention.

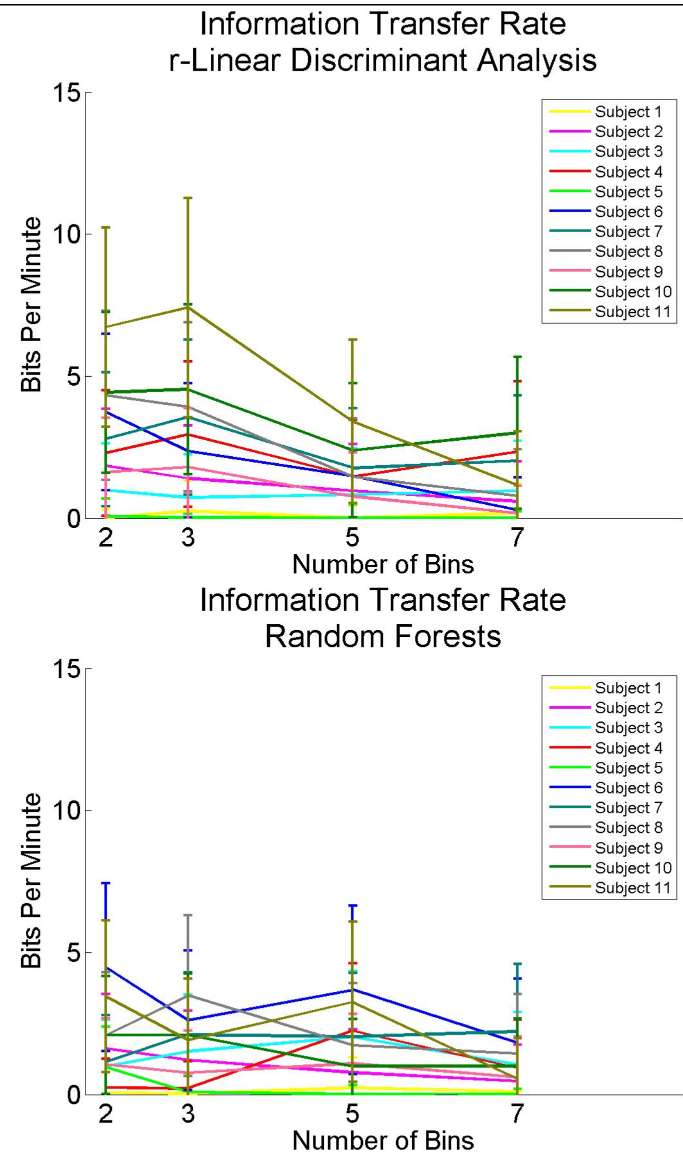

Figure 21: ITRs from the vertical condition at increased discriminant precision
Empirical, expected ITRs and 97.5% CI from Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the vertical tracking was performed with greater granularity (as shown in figure 13). The maximal ITR is seen in the 3-bin case for subject 11. The benefit of tracking with more precision than just discriminating vertical hemifield of attention locus can be clearly seen.

Topographic visualization of models in the three-bin case indicate that alpha, low-beta and high-beta EEG power varied most significantly in the very focused region of occipito-parietal junction over the central sulcus, while gamma band power showed no discerned differences between vertical attention locations (figure 22). Much more activity is seen in these bands and over this region when attention was directed above fixation, while much less activity is seen in this region when attention is directed below fixation. When attention was directed near fixation, activity was at a median value between the higher activity seen when attending upwards and the lower levels of activity when attending downwards. Random Forest feature importance indicated that low-beta activity over this central, occipito-parietal region was by far the most important feature contributing to correct tracking of covert attention locus in the vertical direction.

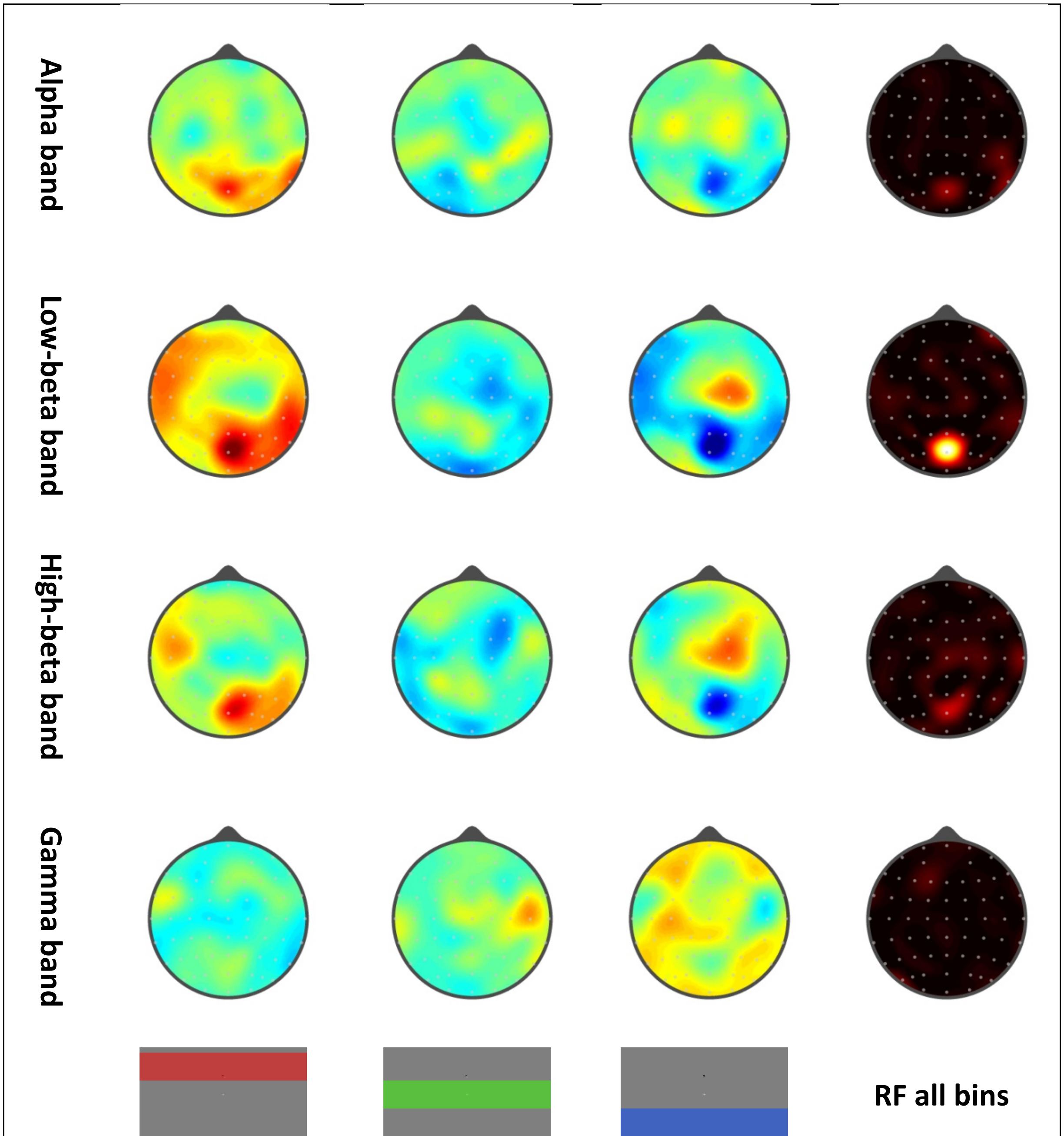

Figure 22: Models from the best-performing subject (11) in the vertical condition
Left: LDA model class means for the 3 bin case. Class means are, from left to right, attention up, attention ahead and attention down. Increased synchrony can be seen in red while desynchrony can be seen in blue. Attention directed above fixation is associated with increased synchrony centrally over occipito-parietal sulcus and the lateral fissure in alpha, low-beta and high-beta bands, while attention below fixation is associated with desynchrony in this region. Attention near fixation is associated with average synchrony values between attention up and attention down.
Right: RF model feature importance supports the importance of this region, within these EEG bands, for correct prediction of covert attention locus.

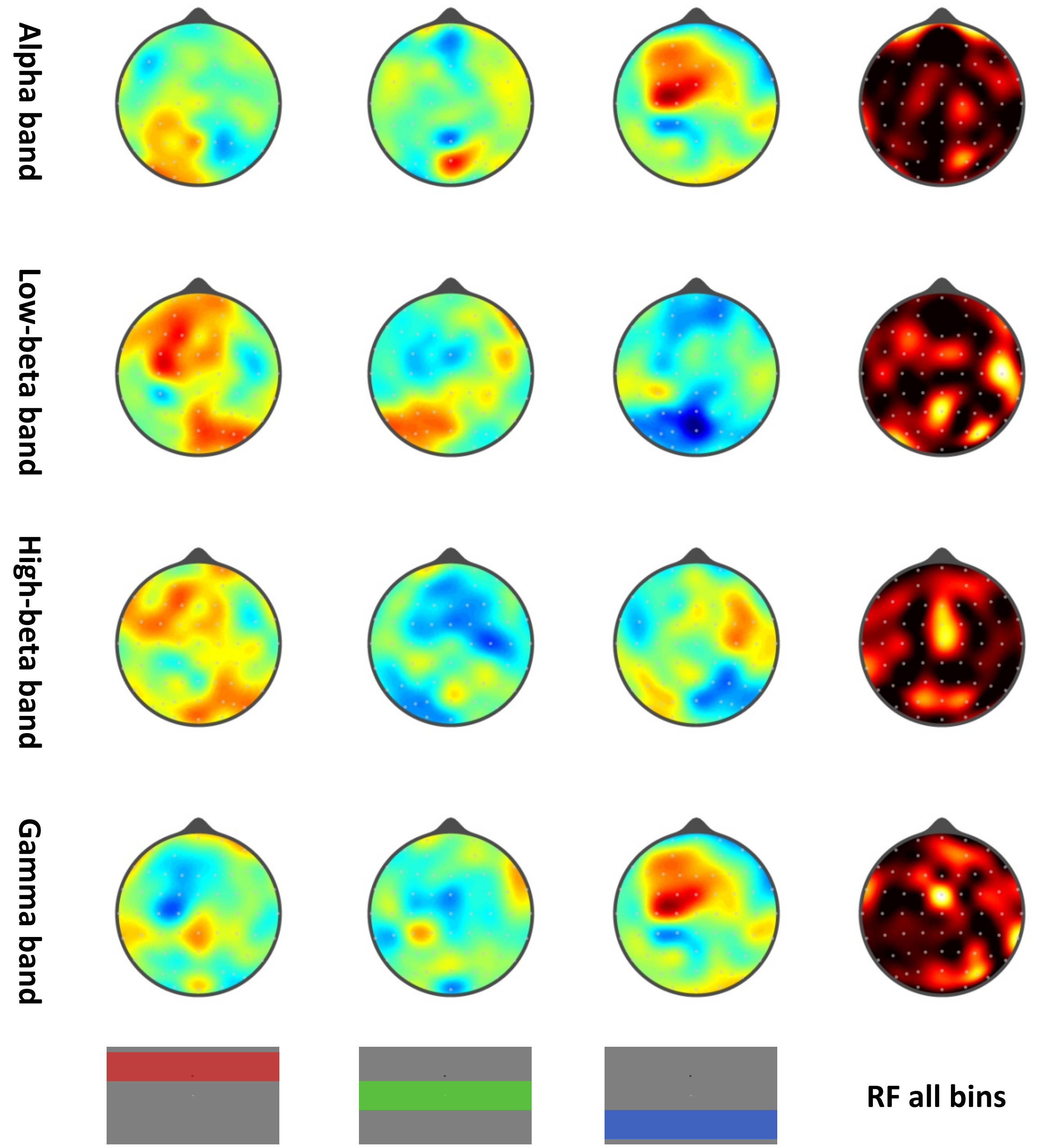

Figure 23: Models from the worst performing subject (5) in the vertical condition
Models fit to data from subjects with poorer predictive performance do not emphasize the central occipito-parietal junction region in the alpha, low-beta and high-beta bands.

Unlike in the horizontal case, confusion matrix analysis shows that tracking attention vertically is a more difficult prospect (figures 24 & 25). Models showed a strong preference to predict attention in the upward direction. In conjunction with the analysis of spectral-spatial activity of EEG contributing to accurate prediction, it is likely that increased activity in alpha, and beta bands was highly indicative of attention being towards the extreme upper region of the visual field, while the characteristic features of EEG power while attention is directed anywhere else along elevation was more difficult to discern.

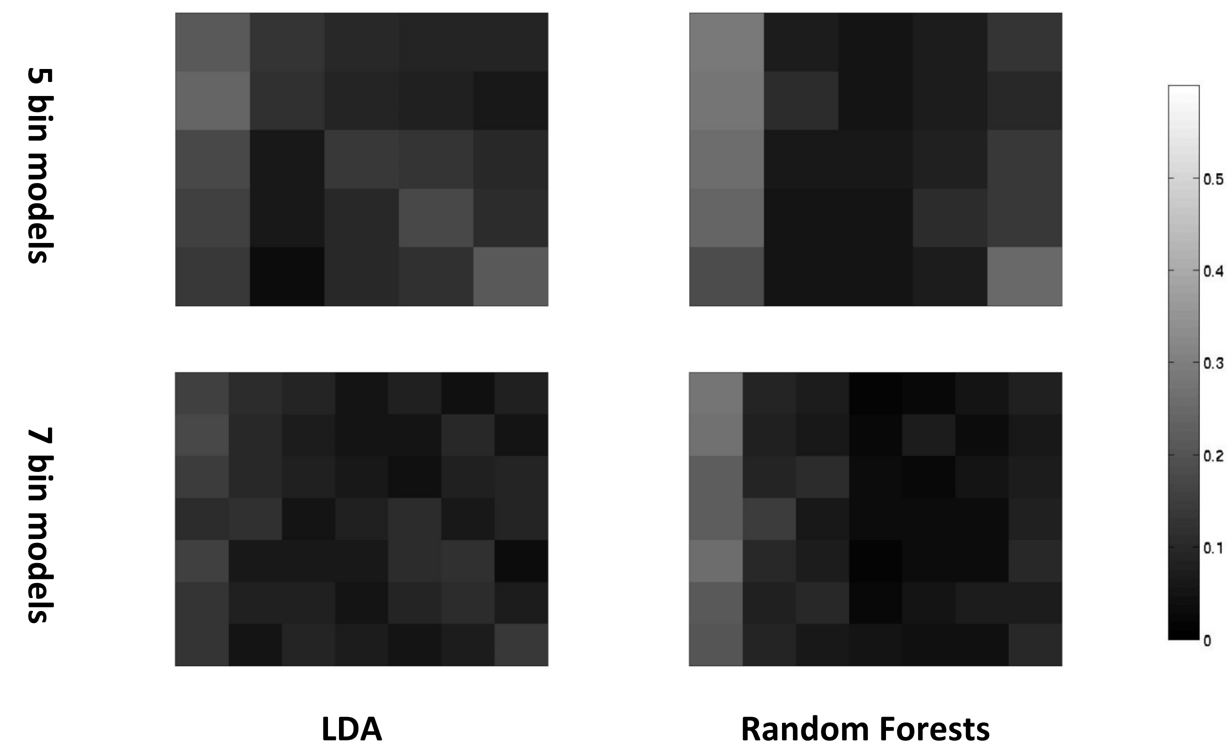

Figure 24: Confusion matrices from the best-performing subject (11) in the vertical condition
Confusion matrices for the vertical condition are displayed with actual attention location along rows, ordered from most top bin to most bottom bin, with probability of predicting a given bin along columns ordered from most top (left) to most bottom (right).
Confusion matrices for all good performing subjects display some block-diagonal structure, but also indicate a strong preference for prediction of the top most attention location.

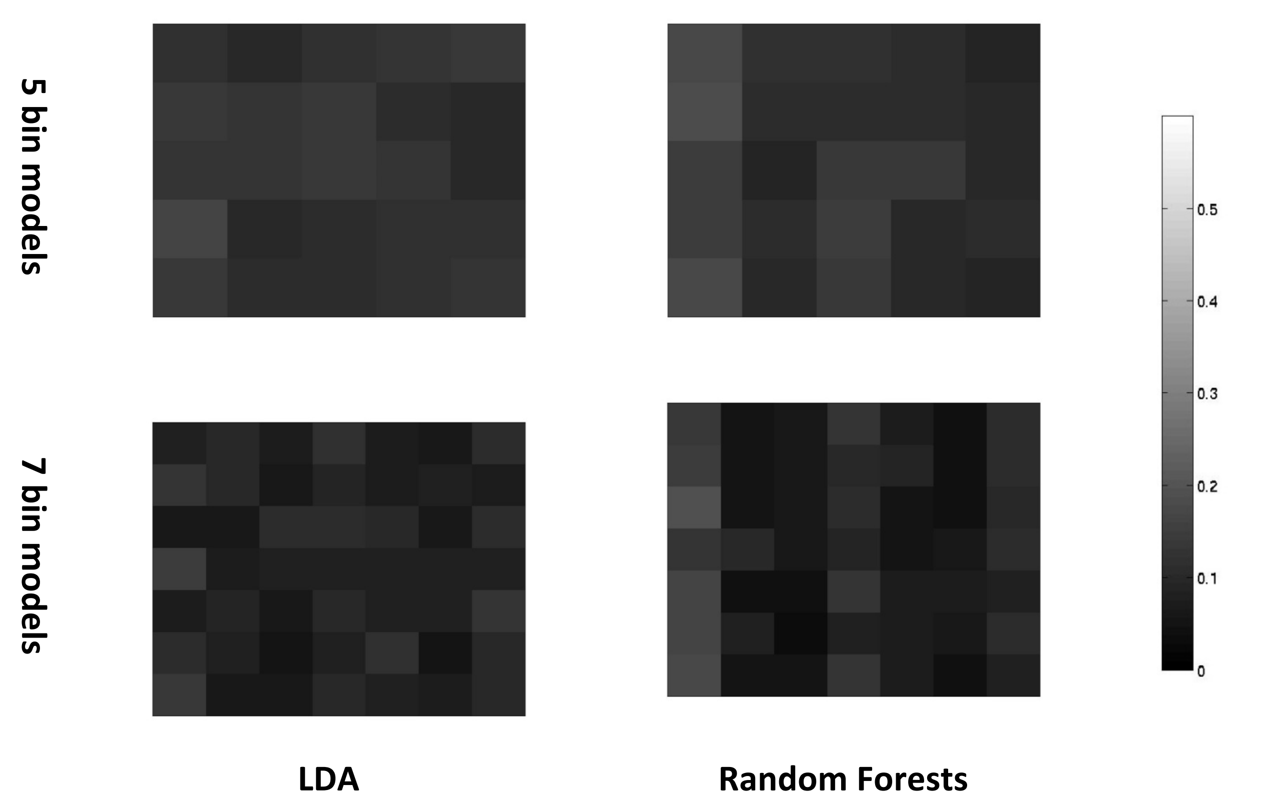

Figure 25: Confusion matrices from the worst-performing subject in the vertical condition
Confusion matrices of poorer performing subjects display a uniform distribution for prediction of any attention location given an actual attention location.

Discussion

Experimental results show that the locus of visual attention can be tracked in one dimension using EEG. Tracking was successful at varying levels of spatial precision when attention location varied horizontally or vertically. The most informative EEG features were found in the low-beta band, between 16 and 20 Hz, over the parietal and occipital lobes. Additionally, alpha and higher-beta band activity in parietal and occipital lobes contributed to increased performance of tracking.

Lateralized occipital and parietal EEG features in alpha and beta bands were most informative when tracking attention to targets with positions that varied horizontally. These results agree with earlier reports that link lateralized alpha and beta band activity to the side-to-side direction of visual attention (Bahramisharif 2011, Gerven *et al*. 2013, Kelly *et al*. 2006, Mangun 1995, Ricco *et al*. 2012, Thorpe *et al*. 2012, Tonin *et al*. 2012 & 2013). EEG activity in the alpha and beta bands of the central, occipito-parietal junction, over the central sulcus, were found to be most associated with attention varying in the vertical direction. This result has not yet been reported in EEG literature, but it agree spatially with magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI) studies of directed visual attention (Bahramisharif 2010 & 2011, Silver 2005).

Tracking accuracy rates found when parsing the visual space into two bins were comparable to those reported for other reported covert attention EEG BCI paradigms (Tonin *et al*. 2012& 2013). For this set of EEG features, regularized-Bayesian Linear Discriminant Analysis outperformed nonlinear Random Forest models in all but a few cases. This indicates that simpler models are likely sufficient to track attention when using CSPs.

The fastest reported communication rates of EEG BCIs, which use endogenous attention signals, fall just above eight BPM with a performance rate of 85% in the best reported subjects, 2.85 seconds of EEG collection per trial and a binary left *versus* right attention choice (Tonin *et al*. 2012 & 2013). Covert attention BCIs of this type are limited in their ITR by the binary nature of their attention location choice. In this experiment, two subjects produced ITRs in excess of eight BPM in the three bin case while tracking attention that varied horizontally. The best ITR seen in this experiment, 11.35, was seen while tracking horizontally varying attention into two bins. The best communication rate seen while tracking attention vertically was 7.42 BPM, while tracking attention into three vertical bins.

Qualitatively, subjects could be grouped into high performers, or those whose attention tracking accuracy rates were consistently above chance, variable subjects whose accuracy rates varied depending on orientation of tracking, and poor performers whose performance was consistently near or at chance accuracy rates. During experimentation, some of the variable subjects reported difficulty directing covert visual-spatial attention in one direction or the other. These difficulties were subject-specific and coincide with reduced performance in the orientation reported as difficult for that subject. Performance of this attention tracking method therefore is influenced by both detectable EEG activity as well as a subject's proficiency in directing gaze-independent, covert visual-spatial attention.

The success of this method encourages further research on the EEG based tracking of bottom-up covert visual-spatial attention for BCI use. Specifically, tracking of attention in two dimensions simultaneously should be attempted.

IV. Tracking attention in two dimensions using EEG

Introduction

The results from experiment two showed that spatial locus of covert, visual attention could be effectively tracked using EEG signals while attention was being directed to targets as they appeared. Tracking was successful while attention varied in one dimension, either the horizontal direction or in the vertical direction. The desirable next step for this research would be to track attention as it varies in more than one dimension. Silver has reported topographic maps of two dimensionally varying covert attention acquired by fMRI (Silver 2005), while Bahramisharif and colleagues have use MEG detect the horizontal and vertical orientation of covet attention and to predict the continuous, radial orientation of attention (Bahramisharif et al. 2010 and Gerven et al. 2009). However, no studies have reported characterizing EEG activity associated with directed, covet attention as it varies in two dimensions.

The present experiment uses much of the methods described in the previous two chapters, but requires the subjects to vary he locus of attention in two spatial dimensions simultaneously. Utilizing the informative EEG power-band features identified in the previous chapter, predictive models will again be used to both characterize EEG activity associated with directed visual attention and evaluate the precision to which locus of attention can be reliably tracked.

Methods

The environment, tools, subjects and experimental procedures used in this experiment are identical to those described in experiment two except for the following differences. Attention target locations were sampled uniformly from the 34° by 34° square area centered on the fixation point (figure 26, top). Targets were again placed at a minimum distance of 2° from the preceding target location. A total of 5040 trials were collected from 12 sessions, each containing 420 trials, over the course of two or three days.

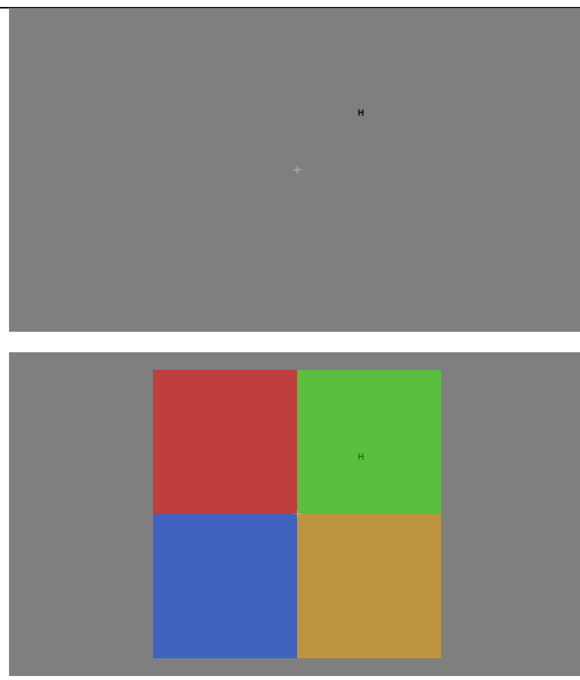

Figure 26: Experiment screen and prediction bins
Top: The display is identical to experiment 2. In the displayed trial, the letter H is the covert attention target. Target locations were sampled uniformly in the square defined by $[-17°, 17°]$ at top-left and $[17°, -17°]$ at bottom-right.
Bottom: The attention target sample space divided into four equal sized bins for classification. Classification was also performed using nine (three x three) bins, 25 (five x five) bins and 49 (seven x seven) bins.

Signal processing and feature extraction methods were identical to those described in experiment two.

As in experiment two, LDA and RF were used for predictive modeling. Classification targets were defined by binning the attention target sampling space on one of two ways. First, the target bins were defined as two dimensional squares numbering either four (two x two), nine (three x three), 25 (five x five) or 49 (seven x seven), with the sides of each bin being of length 17°, 11°, 6° and 4°, respectively (figure 26, bottom). Second, two dimensionally varying attention was tracked in one dimension at a time, in an identical manner as experiment two. Predictive accuracy, ITR, topographies and confusion matrices were computed in the same fashion as in experiment two.

Results

Two dimensional variation in locus of attention

Tracking of attention in two dimensions was successful when the attention space was divided into four or seven equal-sized bins (figure 26). When tracking attention in two dimensions, at these levels of precision, accuracy rates were significantly above chance for all subjects. In the four bin case eight of the 11 subjects posterior accuracy rate lower bound was at least 15% above chance. However, rates of accuracy varied widely from 37.8% to 28.1% as compared to chance of 25% when predicting one of four bins of attention, while accuracy ranged from 19.3% to 12.7% as compared chance of 11.1% when predicting into one of nine equal-sized bins. More precise prediction resulted in accuracy rates barely above chance or not significantly above chance.

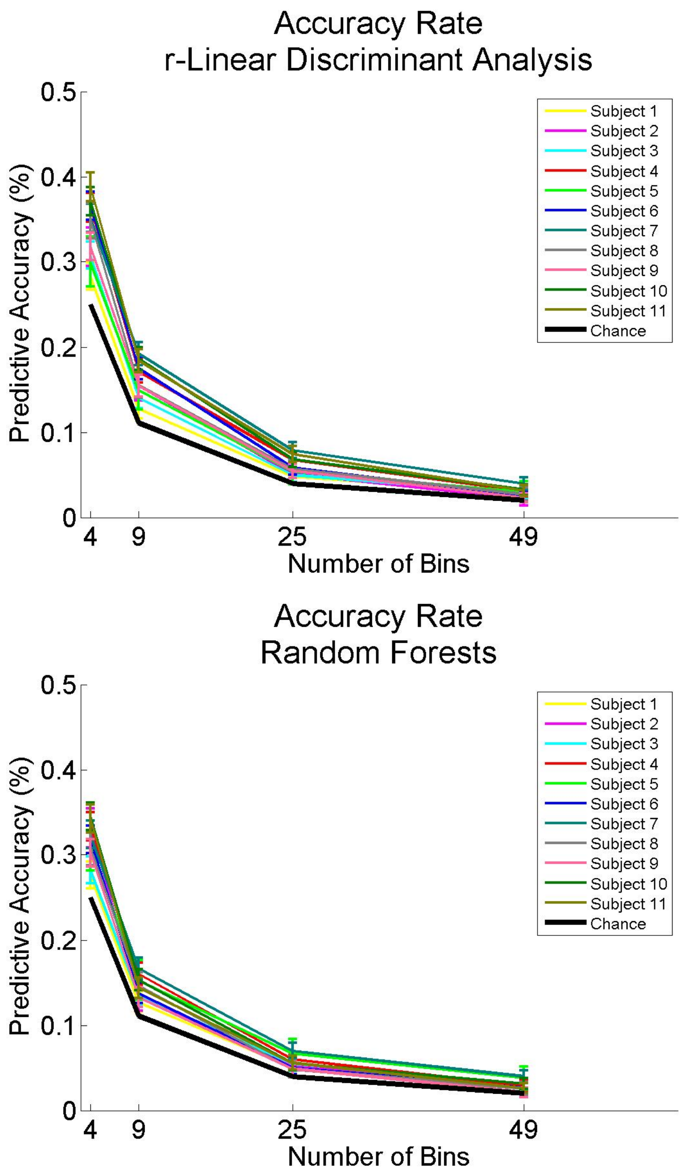

Figure 27: Accuracies when tracking attention in two dimensions

Empirical, expected predictive accuracy and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the two dimensional attention target sample space was divided into more numerous, square bins (as shown in figure 2). Chance accuracy at each number of bins displayed as the bold, black line. Linear models significantly outperform chance prediction rate for all subjects in up to 9, 3 horizontal by 3 vertical, bins. In the case of some subjects, correct attention bin could be predicted at significantly better than chance rate from among 49 different, equal-sized bins. As compared to linear models, nonlinear models performed more consistently across subjects and generally better when trying to predict attention location from among 25 or 49 bins.

ITRs produced from linear models consistently outperformed nonlinear models when tracking attention in two dimensions (figure 28). Additionally, the increased tracking accuracy seen in the four-bin case, (two by two), produced the greatest ITRs. The highest communication seen for two dimensional tracking was 6.65 BPM in the four-bin case from subject 11.

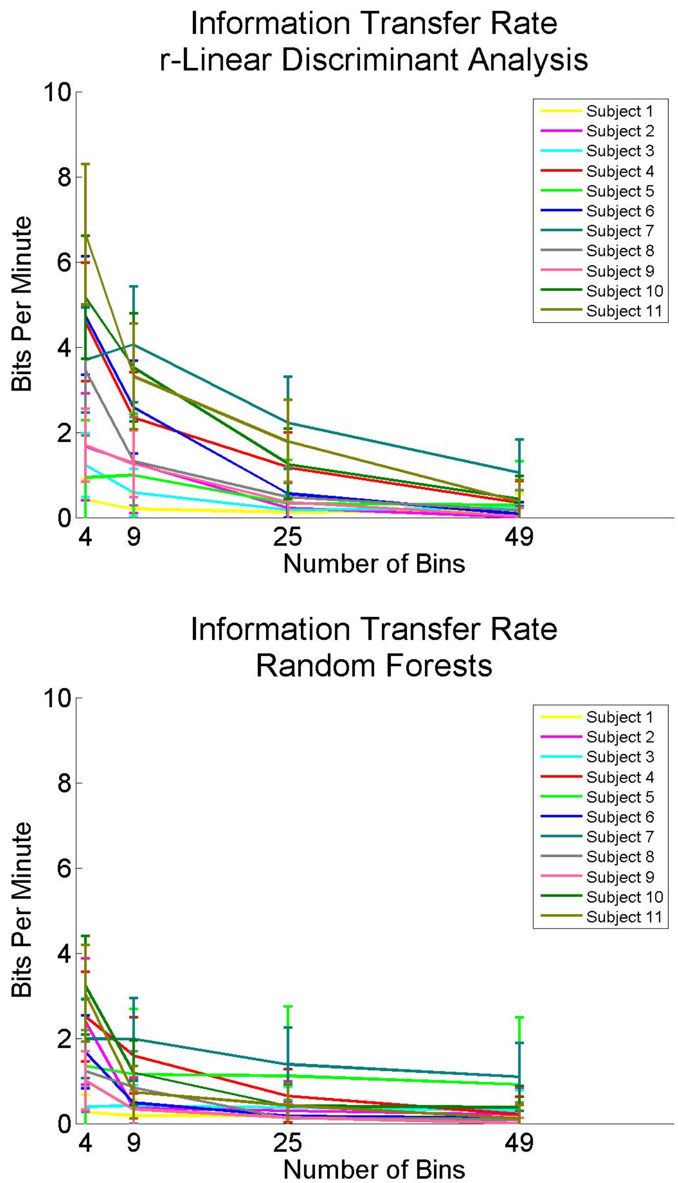

Figure 28: ITRs when tracking attention in two dimensions
The majority of subjects produced maximal ITR in the four bin case (2x2). Increasing the precision to which attention locus is tracked does not aid in ITR when tracking attention in two dimensions.

Visualizing the four-way models again showed parietal and occipital regions in EEG alpha, low-beta and high-beta bands to be most indicative of locus covert attention when it varied in two dimensions (figure 29). Within the linear model class means, diagonally-opposite classes displayed identical spatial patterns with opposite polarity in these bands. Generally, for the two attention-up classes, increased activity was seen in left occipito-parietal regions and decreased activity was seen in right occipito-parietal regions relative to the two attention-down classes. The similarity of spatial patterns with opposite polarity is likely a result of the shared covariance structure between the classes of the linear discriminant models, and inference from these models upon EEG recordable neural activity associated with two dimensionally varying attention should be discouraged. The nonlinear Random Forest models, although with slightly lower overall performance, show the central occipito-parietal region of the low-beta band to be most useful in accurate tracking, followed by right parietal regions in alpha and high-beta bands.

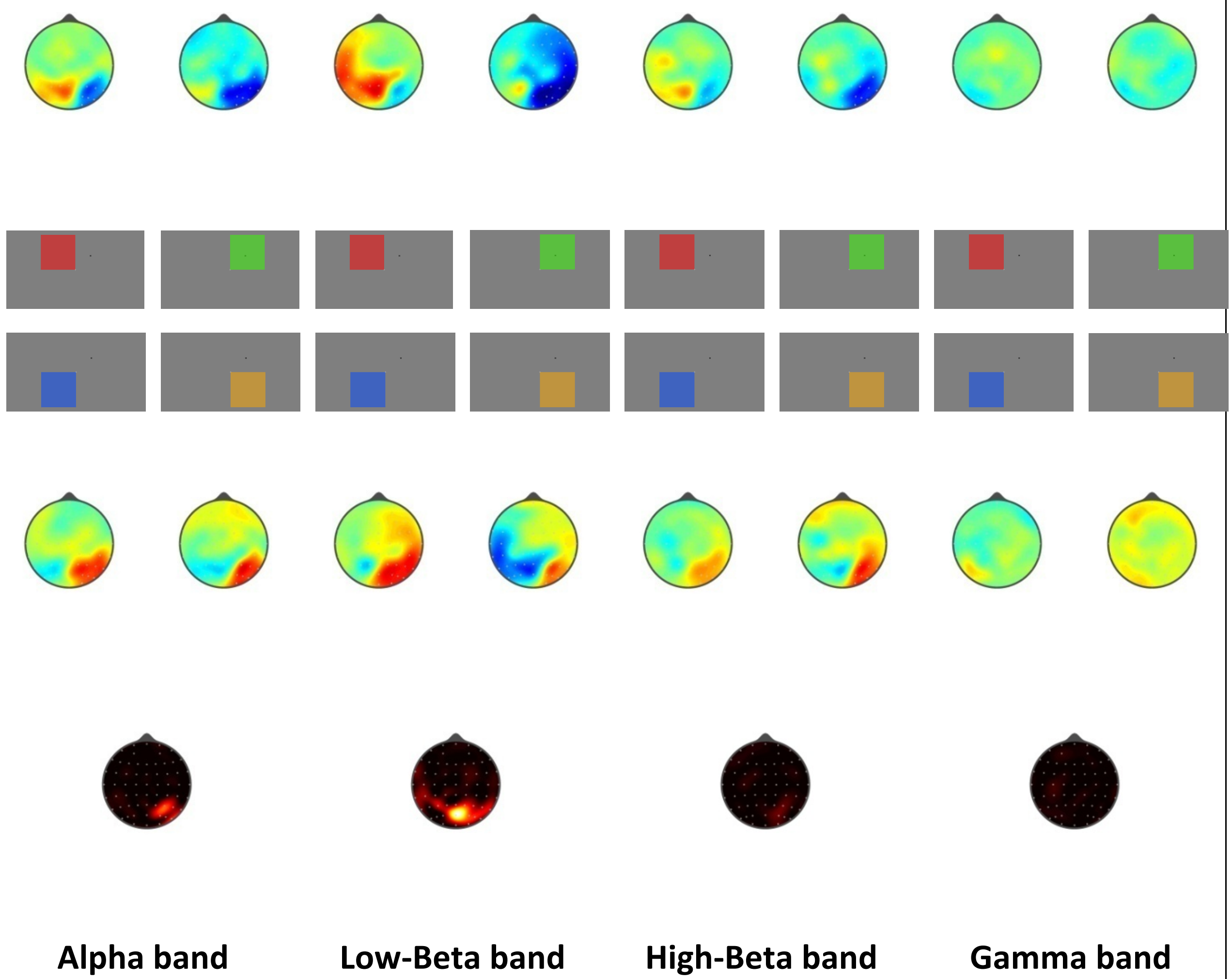

Figure 29: Models from the best performing subject (11) when tracking attention in two dimensions
Top: LDA models fit when attention is varied in two dimensions indicate activation in the occipito-parietal regions seen in models fit to the horizontal and vertically varying attention conditions. Again, models emphasize activity primarily in alpha, low-beta and high-beta bands.
Bottom: RF model feature importance indicates that alpha activity in right parietal and low-beta activity in central occipito-parietal junction contribute most to correct prediction of covert attention locus.

Tracking horizontally in the while attention varied in two dimensions

When tracking the horizontal position of attention while the locus of attention varied in two spatial dimensions, accuracy decreased in some cases and increased in other when compared to tracking in cases where locus of attention varied only in the horizontal direction (figures 14, 30). Tracking accuracy for all subjects exceeded chance, in statistical significance, at all levels of precision when tracking was conducted with linear models, while two failed to exceed chance accuracy when tracking was done with nonlinear models. In the two-bin case, seven of 11 subjects posterior accuracy lower-bound exceeded chance by 15% or more.

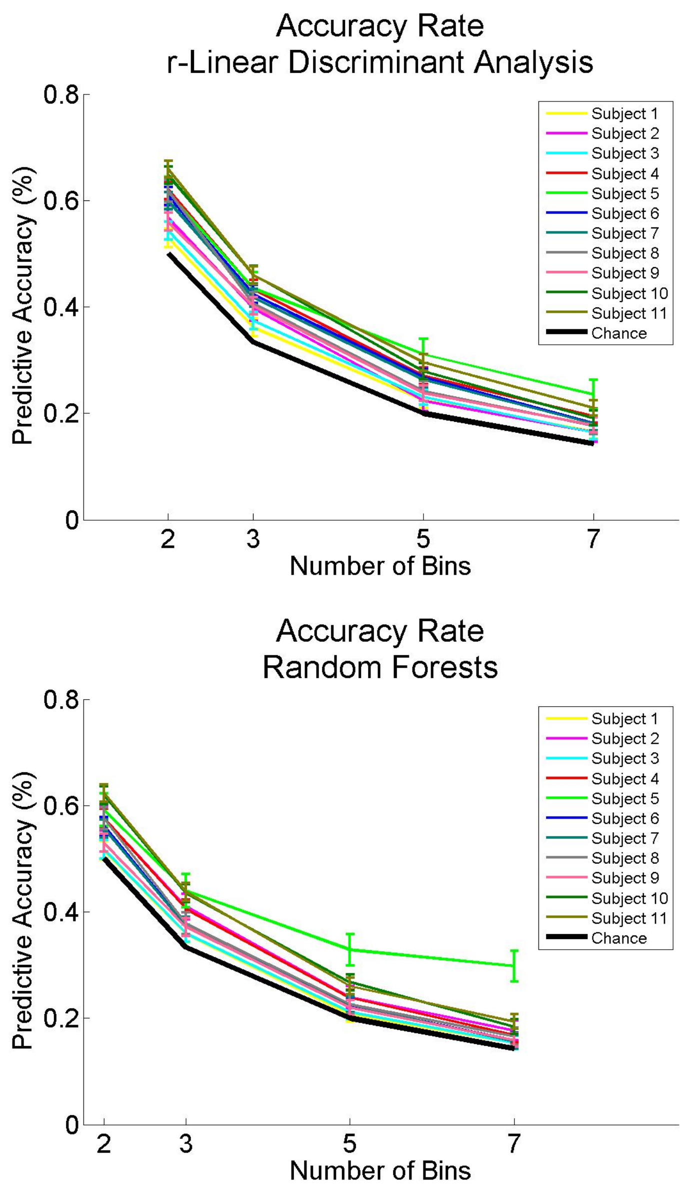

Figure 30: Accuracy rates tracking horizontally when attention varies in two dimensions
Empirical, expected predictive accuracy and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the two dimensional attention target sample space was divided into vertical bins similar to that used to analyze the horizontal condition (figure 1). Chance accuracy at each number of bins displayed as the bold, black line. Linear models significantly outperform chance prediction rate for all subjects in up to seven bins. Nonlinear model predictions were less accurate than linear model predictions in all subjects except subject 3. Subject 3's locus of attention could be predicted with significantly more accuracy in the five and seven bin case with using nonlinear models.

The pattern of communication rates followed that seen in tracking horizontally varying attention, with a reduction in performance (figures15, 31). Subject 5 performed exceptionally well when Random Forests were used to track their attention in the five-bin and seven-bin cases, and as a result the communication rates were 6.59 BPM and 11.18 BPM. These improved ITRs display the benefit of attempting to track locus of attention more precisely.

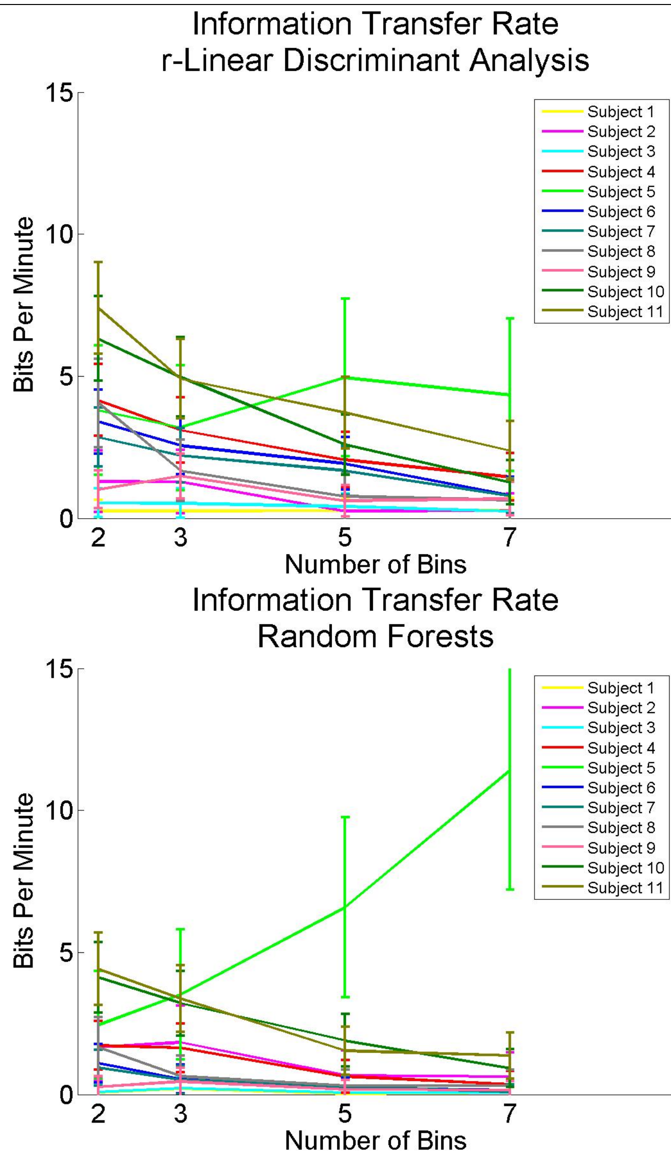

Figure 31: ITRs tracking horizontally when attention varies in two dimensions

ITRs for tracking locus of attention horizontally while it varies in two dimensions are below that seen when tracking attention that varies only horizontally. For most subjects, maximal ITR is seen in the two-bin case, indicating increased granularity of tracking does not yield increased communication speed.

Visualization of the horizontal tracking models of two dimensionally varying covert visual spatial attention, in the three-bin case, revealed activation patterns similar to attention tracking when attention varied only in the horizontal dimension (figures 16, 32). Attention towards the left or the right visual fields was associated with relatively more activation ipsilaterally and less activation contralaterally in occipito-parietal alpha, and beta bands while attention near fixation was associated with relatively less alpha, and low-beta and high-beta band power bilaterally in occipital and parietal lobes. Random Forest model feature importance also found the lateral parietal regions of alpha and beta bands to be most important for correct attention locus tracking, with changes in low-beta activity in lateral parietal lobe to be the most crucial features in correct prediction.

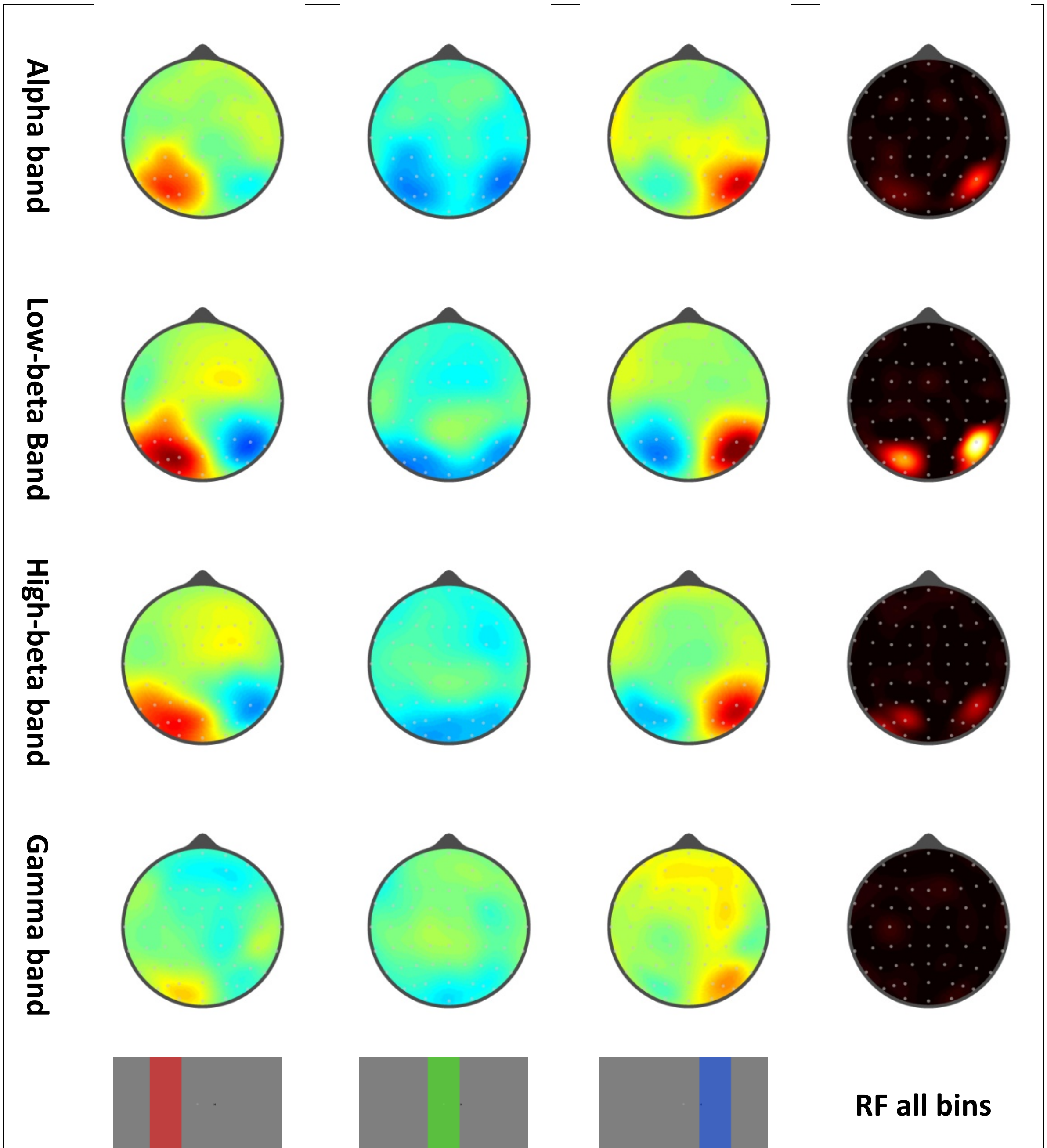

Figure 32: Models from the best-performing subject (10) when tracking horizontally while attention varies in two dimensions

Results of analysis of vertical margins for the two dimensional condition are comparable to the horizontal condition. LDA models (left) display ipsilateral synchrony as well as contralateral desynchrony in alpha, and beta bands while attention near the horizontal position of fixation display bilateral desynchrony. Additionally, RF models indicate parietal and occipital alpha and low-beta bands contribute most to accurate prediction attention locus.

Confusion matrices for the horizontal tracking of two dimensionally varying covert spatial attention also displayed the near-block-diagonal structure seen in horizontal tracking of one dimensionally varying attention (figures 8, 24).

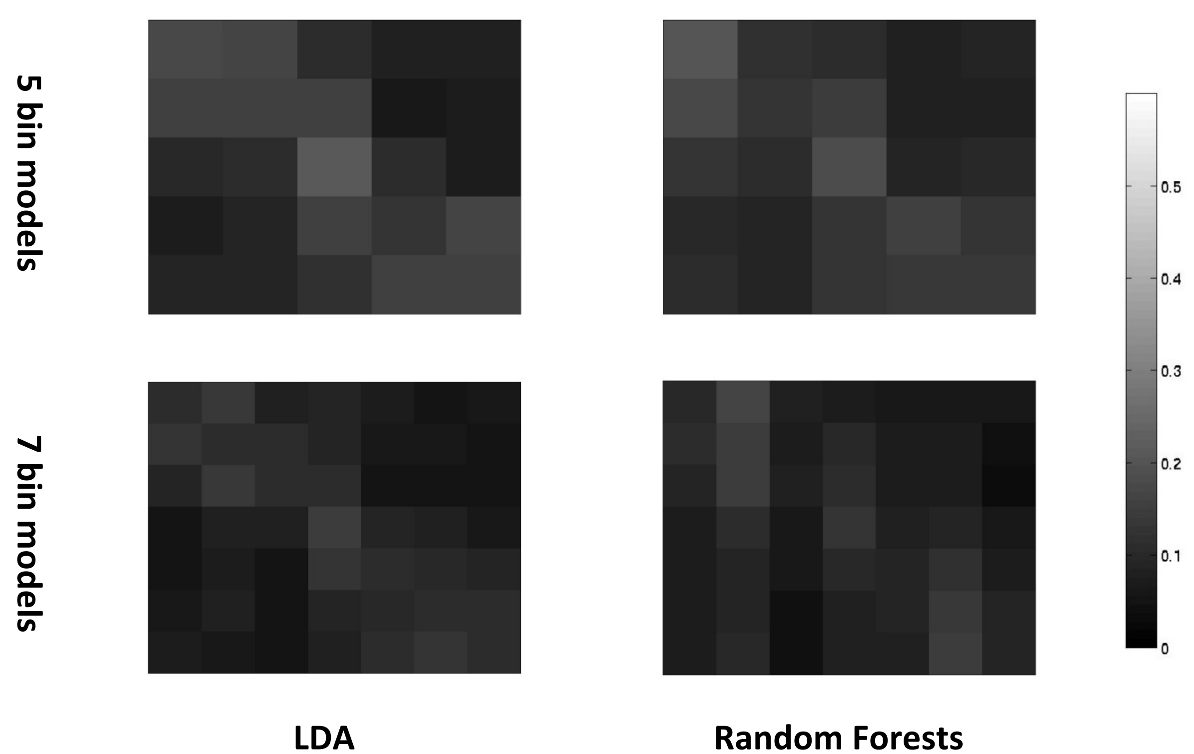

Figure 33: Confusion matrices from the best-performing subject (10) when tracking horizontally while attention varies in two dimensions

When predicting the vertical marginal bin of attention location when locus varied in two dimensions, confusion matrices again display a block-diagonal structure similar to horizontal condition (figure 8).

Tracking vertically while attention varied in two dimensions

When tracking locus of covert visual attention vertically while subject's attention varied in two dimensions, the same pattern of reduced accuracy in the best performers and increased accuracy in the worst performers can be seen (figures 20, 36). Only one subject's performance consistently failed to exceed chance, while a second subject's performance decreased below chance when prediction was made into five or seven bins of the vertical sample space. In most cases, performance was below that of horizontal attention tracking under the two dimensional conditions. In the two bin case, four of the 11 subject's posterior accuracy rate lower-bound exceeded chance by at least 15%.

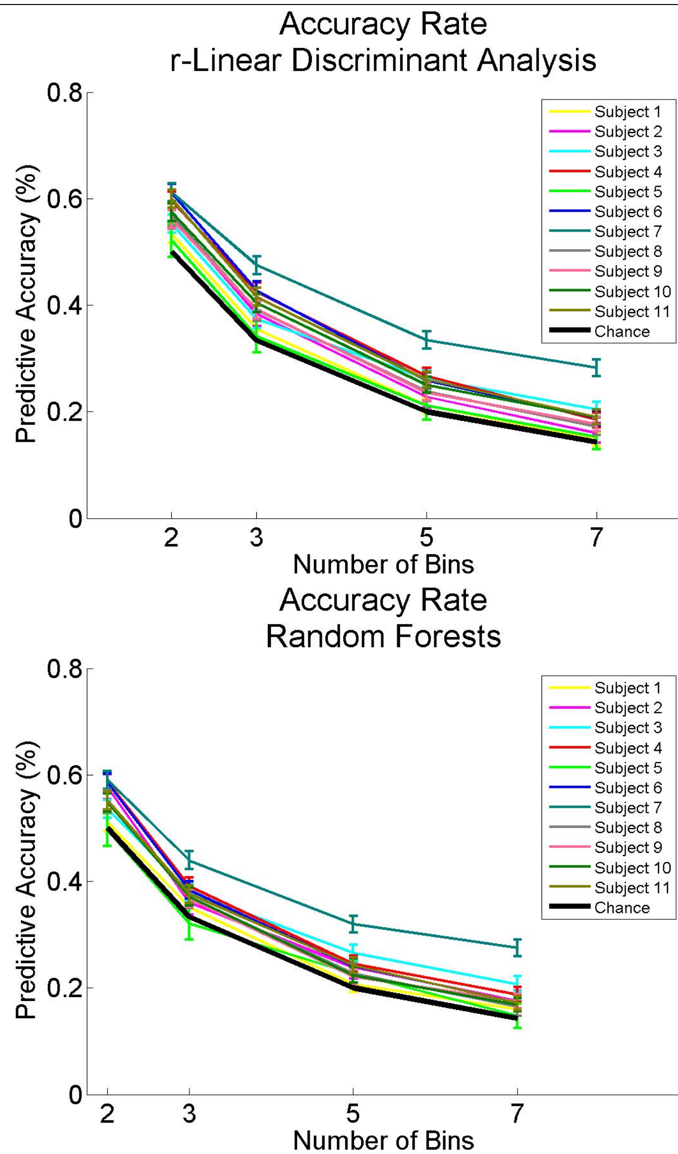

Figure 34: Accuracy rates tracking vertically when attention varies in two dimensions

Empirical, expected predictive accuracy and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom) as the two dimensional attention target sample space was divided into horizontal bins similar to that used to analyze the vertical condition (as shown in figure 1). Chance accuracy at each number of bins displayed as the bold, black line. Linear models significantly outperform chance prediction rate for all subjects in up to seven vertical bins. In most cases linear models outperformed nonlinear models.

Communication rates for tracking attention vertically while it varied in two dimensions can be seen in figure 35. Like in the horizontal tracking of two dimensionally varying attention, one subject's accuracy rate declined more gradually as tracking was performed more precisely. This subject's ITR increased in the three-bin to seven-bin cases. This subject producing a maximal ITR of 9.37 BPM when linear models discriminated between seven bins of attention location along elevation. The remainder of the subjects produced maximal ITRs in either the two-bin or three-bin cases, and these ITRs were generally lower than those seen when tracking attention varying only in the vertical direction.

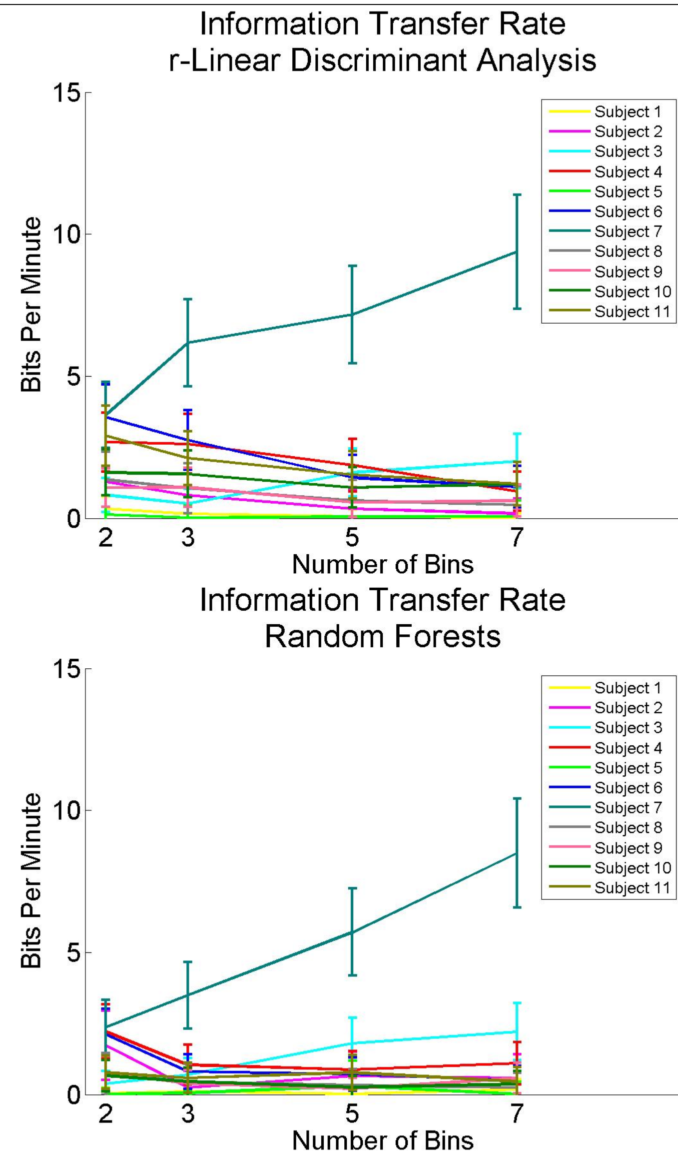

Figure 35: ITRs tracking vertically while attention varies in two dimensions

Empirical, expected ITR and 97.5% CI of Linear Discriminant Analysis models (top) and nonlinear Random Forest models (bottom). ITR is less than the comparable rates when attention is varied only in the vertical direction. The increasing ITR of subject 7 nicely demonstrates that when discriminating attention locations between more numerous bins, mild increases in predictive accuracy rate results in a large increase in communication speed.

Topographic visualization of these models showed very similar activity patterns to one dimensional vertical tracking. The most significant features, and those most important to successful tracking, varied in the very concentrated region of the occipito-parietal junction over or near the central sulcus in the alpha, and beta bands (figures 22, 36). In the case of vertical tracking while attention varied in two dimensions, the low-beta band, and to a lesser degree the high-beta band contributed most to successful tracking when using Random Forests, while variance in alpha activity had much less effect on performance.

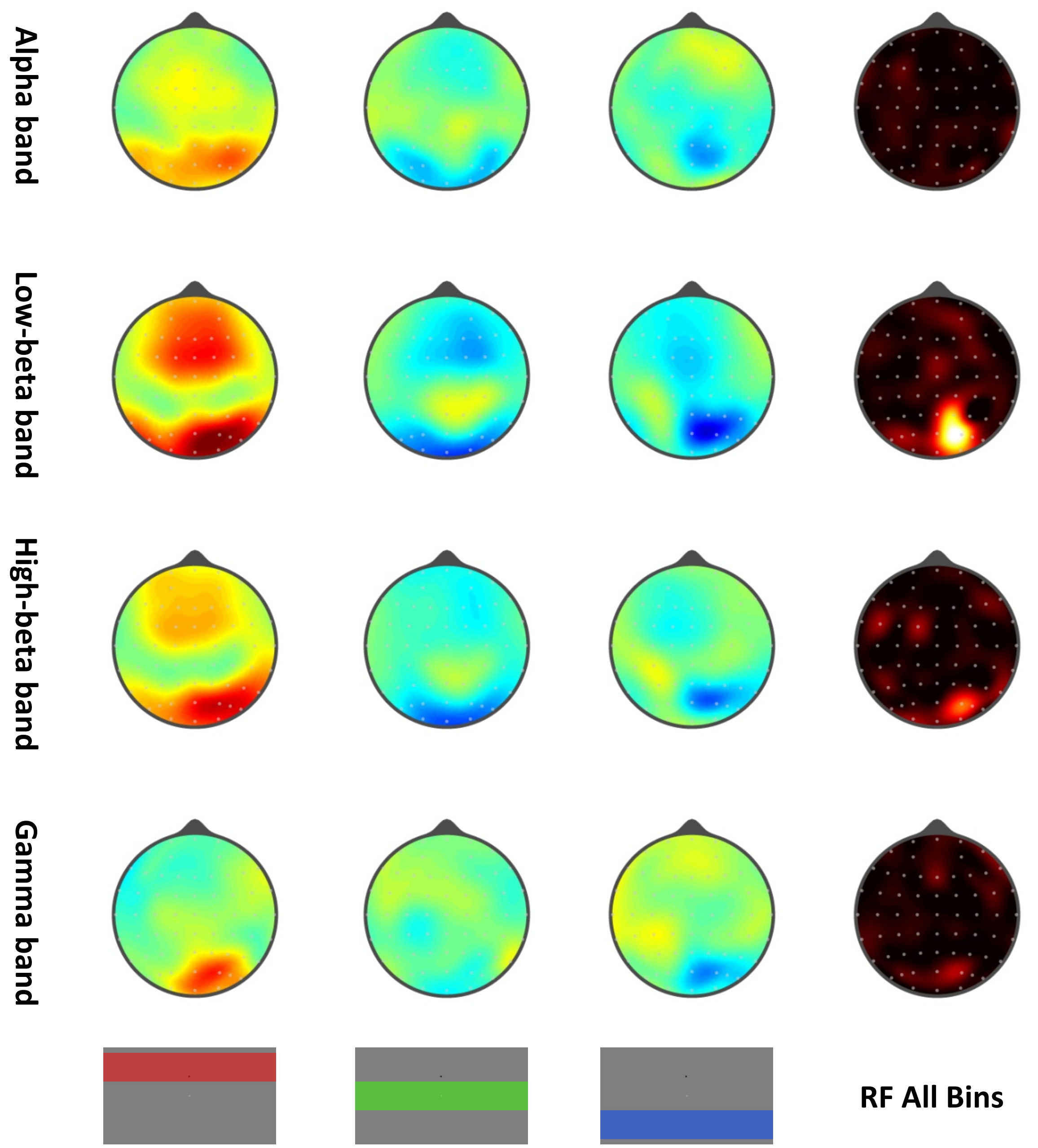

Figure 36: Models from the best-performing subject (10) when tracking vertically while attention varies in two dimensions

Results of analysis of horizontal margins for the two dimensional condition are comparable to the vertical condition. Again, LDA models (left) of attention up display synchrony in the occipito-parietal junction above the lateral fissure in alpha, and beta bands while attention down shows desynchrony in this region. RF model feature importance indicates low and high-beta in central occipito-parietal junction provides the most informative features for correct prediction of attention locus.

Confusion matrices for both linear and nonlinear models displayed a strong preference for the maximally upper, central and maximally lower bins of the vertical attention space giving rise to the vertically stripped pattern seen (figure 37).

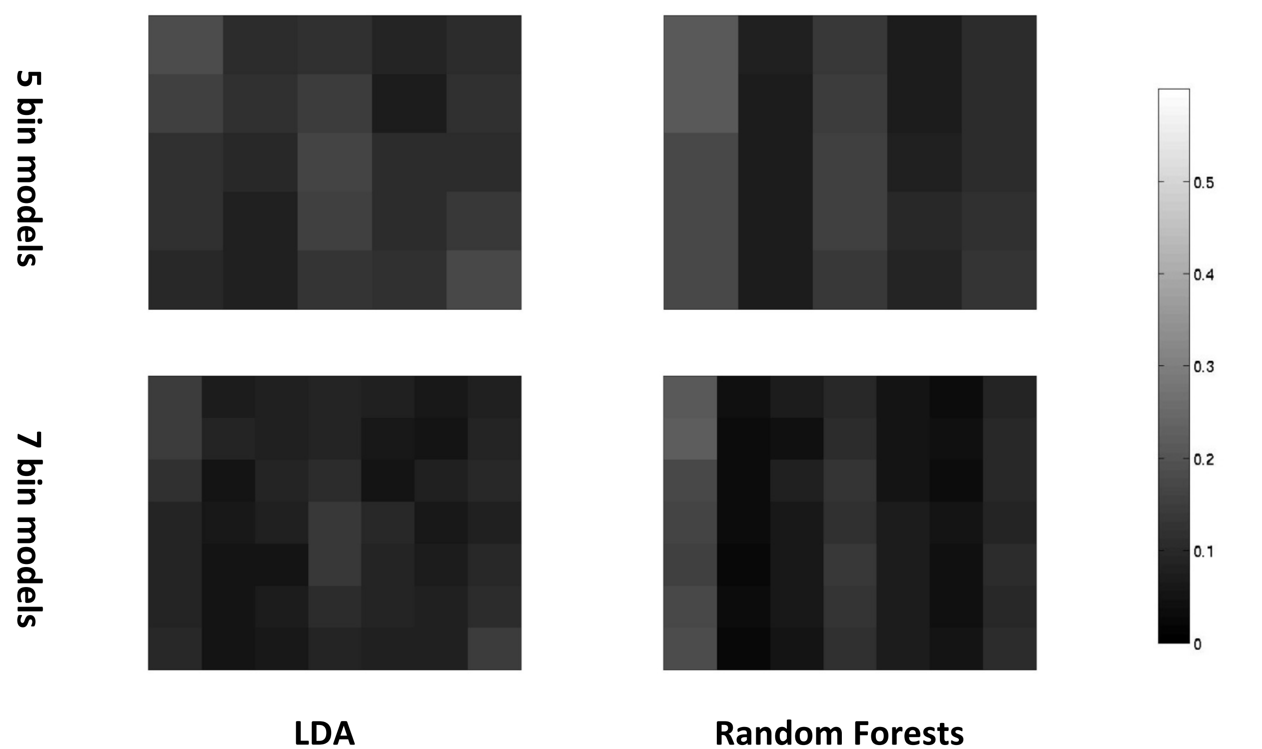

Figure 37: Confusion matrices from the best-performing subject (11) when tracking vertically while attention varies in two dimensions

When predicting the horizontal marginal bin of attention when attention locus varied in two dimensions, confusion matrices display a preference for predicting attention is either near fixation (central column) or at the extreme top or bottom of the visual field. Such a preference indicates model difficulty discriminating locus of covert attention in the vertical direction unless it is very near or very far away from fixation.

Discussion

Using the methods described, attention could be tracked in two dimensions using EEG, at rates significantly above chance in up to 49 (seven x seven) distinct regions of the visual field, for all but a few of the subjects tested. ITRs reported for the four-bin case of two dimensional attention tracking approach the best reported communication rates seen from EEG BCI literature utilizing endogenous, top-down attention signals (Tonin *et al*. 2012& 2013). Though accuracy rates were above chance, the rates are by no means high enough to be used in an online BCI. However, these positive results encourage further research towards using endogenous brain-activity associated with attention directed at non-specific targets for BCI control. These signals can be used to predict attention locus more precisely than in the binary fashion used so far in EEG BCI research. More precise prediction of attention location will lead to many fold increases in communication rates once accuracy rates can be improved.

A combination of the important EEG features found for horizontal and vertical tracking contributed to successful tracking of attention in two dimensions. Variation in lower-beta band activity centrally located at the occipito-parietal junction, over the central sulcus, contributes most to successful tracking. Additionally, right lateralized, parietal alpha and low beta activity provide additional information regarding position of attention. These results are novel, as there is no literature reporting the EEG activity associated with directed, bottom-up covert attention, in one or two dimensions. However, previous MEG and fMRI literature regarding two dimensional, top-down directed, covert attention agree spatially with these results (Bahramisharif 2010 & 2011, Silver 2005).

Tracking of attention in one dimension while attention varied in two dimensions also proved successful. Regions and EEG bands implicated by predictive modeling agree with the results from experiment two, where attention varied in only one dimension. Accuracy rates, and resultantly ITR, are not-surprisingly reduced compared to when attention varied in only one dimension. Such a reduction in accuracy must be the consequence of brain activity associated with variation in attention position in the untracked dimension introducing irreducible noise in the EEG feature set used for tracking. Despite the reduced accuracy, tracking attention on one dimension while allowing subjects to vary attention location in two dimensions is more directly useful as a passive BCI. Such a BCI could be immediately used to track attention locus to vertical or horizontal bands while a subject performed any fixed-gaze task.

V. Conclusion

Experimental results show that the locus of visual attention can be tracked using EEG. Attempts to track attention using SSVEP-like signals induced from peripheral, unattended flickering stimuli in experiment one were not successful. The highly salient, flickering stimuli were effectively suppressed while attention was directed at intermediate locations, and induced no detectable SSVEP-like signal. However, despite the failure of this method to produce SSVEPs, tracking was still successful when using endogenous alpha and beta band power lateralizations associated with directed, covert attention.

Tracking was successful at varying levels of spatial precision when attention location varied horizontally, vertically or in two spatial dimensions. The most informative EEG features were found in the low-beta band, between 16 and 20 Hz, over the parietal and occipital lobes. Additionally, alpha and higher beta band activity in parietal and occipital lobes contributed to increased performance of tracking.

Qualitatively, subjects could be grouped into high-performers, or those whose attention tracking accuracy rates were consistently above chance, variable subjects whose accuracy rates varied depending on orientation of tracking, and poor performers whose performance was consistently near or at chance accuracy rates. During experimentation, some of the variable subjects reported difficulty directing covert visual-spatial attention in one direction or the other. These difficulties were subject-specific and coincide with reduced performance in the orientation reported as difficult for that subject. Performance of this attention tracking method therefore is influenced by both detectable EEG activity as well as a subject's proficiency in directing gaze-independent, covert visual-spatial attention.

Evaluating the performance in tracking the locus of attention at increased degrees of precision is an attempt to approach the goal of continuously tracking the position of covert, visual-spatial attention in two dimensions. This goal would allow for the use of covert attention as a cursor-like control signal for EEG BCIs. Such a control method would allow or fully functional interfaces for BCI users like those found in modern, user-friendly computer interfaces. In experiment three, tracking the one dimensional position of bottom-up attention could be accomplished at rates significantly better than chance in the majority of subjects in up to seven discrete bins of visual space. Tracking the two dimensional position of bottom-up covert, visual-spatial attention was also at above chance rates.

The success of this method encourages further research on the EEG based tracking of bottom-up covert visual-spatial attention for BCI use. Tracking of two dimensionally varying attention in a single dimension in a passive manner, as shown in experiment three, could easily be implemented in an online EEG BCI, as is, to detect attention locus relative to gaze. Additionally, further research on method should involve experimental displays with more rich backgrounds such as distracter targets or live scenes to evaluate tracking in a more complex environment. Improvements in EEG feature extraction and predictive model building to increase accuracy should also be goals for further research. With improved features, tracking of attention locus should increase in granularity towards the goal of predictive regression modeling of absolute position of bottom-up covert visual attention.

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VII. Appendix